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The importance of STEM: How Rust Belt universities can drive economic growth by supporting high-technology industry

Robert O'Gara

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Robert O'Gara

Accepted for Honors
(Honors)

John Parman, Director

John McGlennon

Peter McHenry

Williamsburg, VA
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Abstract

This study examines whether universities in mid-sized "Rust Belt" cities can help drive local economic growth by directly supporting growth in local high-technology industry. This study is inspired by the hypothesis of van Agtmael and Bakker (2016) that high-technology industry can generate significant levels of economic growth that revitalized Rust Belt communities. This study shows that some university outputs, like undergraduate students in STEM fields and R&D expenditures in STEM fields benefit a Rust Belt city's high-technology industry sector and overall economy. However, these results are stronger in the mid-sized Rust Belt cities of the Midwest rather than those of New England.

Keywords: Rust Belt, High-technology industry, University, STEM

Introduction

In the first half of the 20th century, the Midwest and New England formed the industrial backbone of the American economy, as these two regions produced most of America's manufacturing output. Over time, however, the manufacturing centers in these "Rust Belt" states declined as competition from other regions of the United States and around the world drove them out of business. Alder, Lagakis, and Ohanian (2016) note that while the Rust Belt's share of American manufacturing employment was 51% in 1950, by 2000 that figure dropped to 34%. And in traditionally strong manufacturing industries including steel, automobiles, and rubber tires, the Rust Belt share of American manufacturing employment declined from 75% in 1955 to 55% in 2000 (Alder et al., 2016). Alder et al. blame much of the decline of Rust Belt manufacturing on the lack of competitive pressures on the industry, which in turn led to reduced levels of innovation and productivity. While some Rust Belt cities successfully transitioned away from manufacturing, many mid-sized Rust Belt cities struggled to adapt. These Rust Belt cities are looking for new ways to revitalize their struggling economies as a result.

At the same time, the American university plays a much more important economic role than it did 70 years ago. In the realm of economic development, universities today are anchor institutions with the ability to generate significant economic activity in the local community. Economists see universities as important for local economic development due to their ability to generate human capital, create knowledge, promote knowledge transfer, and exhibit regional leadership among other qualities (Goldstein, Maier, & Luger, 1995).

Universities are also becoming more invested in Science, Technology, Engineering, and Mathematics (STEM) fields. Policymakers on the national, state, and local level see STEM education and research and development (R&D) as key drivers of economic growth, and are further encouraging investments in STEM education and in STEM R&D. A 2011 report from the National Governor's Association highlighted the importance of STEM fields in economic growth, arguing that "STEM occupations are among the highest paying, fastest growing, and most influential in driving economic growth and innovation" (National Governors Association, 2011). STEM education matches well with so-called "high-technology" industries that are focused on STEM fields. Wolf and Terrell (2016) define "high-technology" industry as an industry with "high concentrations of workers in STEM occupations." In the Northeast and Midwest, many Rust Belt cities see high-technology industry as a way to enhance local economic growth.

This study seeks to determine ways in which local universities can enhance the economies of mid-sized, Rust Belt cities in the American Midwest and in New England, particularly by focusing on the impact of university outputs on high-technology industry. Many of these cities have declined significantly due to the loss of manufacturing industries and an inability to successfully transition their economies towards other industries. Of these cities, some have attempted to enhance their local economy by focusing on high-technology industries that are dependent on both skilled workers educated in STEM fields and R&D activities in STEM fields. Through quantitative and qualitative analysis, this study assesses which STEM-oriented university outputs can improve the economies of their respective cities through a well-developed high technology industry.

To examine the relationship between university outputs in STEM fields and both local high-technology industry and the local Rust Belt economy, I first discuss previous literature regarding the economic impact of high-technology industry, the economic impact of universities, and the impact of universities on high-technology industry. Then, I describe the data collected and methodology used for multiple linear regression analysis. I explain the regression output and interpret the results to explain the quantitative impact of university outputs. Specifically, I use multiple regression models to determine the impact of university outputs on high-technology employment, high-technology wage levels, overall employment, and overall wage levels. The regression output indicates that while some university outputs focused on STEM education have a positive impact on employment and wage levels, others do not. I then run stratified regression models by geographic region and find that the results for Midwestern cities better matches the results of the overall models and that the results for New England cities are very different from those of the overall models. To better describe the quantitative results, I provide case study examples which use qualitative analysis to examine the different strategies used by Rust Belt cities. Examining the cities of Akron, Ohio and Springfield, Massachusetts shows ways in which universities can help enhance local high-technology industry growth and overall economic growth. These case studies also explain regional differences between Midwestern and New England Rust Belt cities revealed by the stratified regression models. I conclude by summarizing the research findings and highlighting areas of potential future research.

Literature Review

This literature review examines the existing literature on three different aspects of this study. First, I examine the literature on the economic impact of high-technology industry. Then I examine the literature on the economic impact of higher education. Lastly, I examine the impact of higher education on high-technology industry. These three components of the literature match this study's focus on the impact of university outputs on high-technology industry as well as the focus of higher education on the local economy as a whole for Rust Belt cities. I conclude the literature review by highlighting this paper's role in the literature.

Economic Impact of High-Technology Industry

The inspiration for this study largely comes from *The Smartest Places on Earth* by van Agtmael and Bakker (2016), who argue that the revitalization of former rustbelt areas is increasing the level of economic competitiveness in the United States and in Europe, as these rustbelts become "brain belts" that are centers for high-technology industry. van Agtmael and Bakker describe brain belts both in terms of collaborative partnerships, in which businesses and universities work together to invent new technologies, and in terms of advanced manufacturing. They ultimately recommend that Rust Belt cities become brain belt cities as a successful strategy to revitalize their struggling economies.

For Rust Belt cities to become brain belt cities, van Agtmael and Bakker put forward the hypothesis that investments in high-technology industry generate a wide range of economic spillovers that support the entire economy of a Rust Belt community. To support their argument, they cite examples of successful brain belts and examine how exactly their high-technology business clusters developed. One example they cite is the SUNY Poly College of Nanoscale Science and Engineering's NanoTech Complex in Albany, New York. The NanoTech Complex brings leading computer chip businesses, such as Intel, IBM, Nikon, Samsung, TSMCS, and GlobalFoundaries, to Albany to conduct advanced computer chip research alongside SUNY Poly faculty and graduate students (van Agtmael & Bakker, 2016, p. 62). The presence of the NanoTech Complex encouraged GlobalFoundaries, one of the world's largest independent semiconductor foundries, to create a $10 billion advanced manufacturing facility in the town of

Malta, twenty miles away from Albany (van Agtmael & Bakker, 2016, p. 65). van Agtmael and Bakker contend that the presence of SUNY Poly, its graduate students, and its NanoTech Complex helped create this Hudson Valley brain belt defined by the GlobalFoundaries' advanced manufacturing facility and other semiconductor businesses, which in turn improved the local economy. van Agtmael and Bakker therefore contend that investments in high-technology industry, if done properly, can create brain belts that lead to massive spillover benefits that improve the entire local economy.

Gittell, Sohl, and Tebaldi (2014) research the impact of entrepreneurship in high-technology industries on job growth in American MSA's from 1991 to 2007. Gittell et al. use a standard multivariate regression model to find that a 1% increase in entrepreneurship correlates with a 0.7% increase in employment. These findings also suggest that the growth of high-technology industry, not the concentration of high-technology industry, drive local job growth. As a result, Gittell et al. conclude that above-average levels of entrepreneurship and growth in high-technology industries will spur job growth in an MSA.

Riddel and Schwer (2003) use the endogenous growth model of Romer (1990) to determine the impact that high-technology workers have on state innovative capacity in the United States. Their research finds that a 1% increase in the stock of patents in a state corresponds to a 0.15% increase in innovative capacity, as measured by the number of new patents in the state. Riddel and Schwer claim this increase reflects a "standing on shoulders effect," in which the stock of ideas impacts the rate of new-idea generation. Additionally, a 1% increase in the number of university degrees issued leads to a 0.26% increase in new patents. However, Riddel and Schwer find that the amount of university R&D did not have a statistically significant impact on innovative capacity. They also find that a 1% increase in the number of patents correlates to a 1.12% increase in the number of high-technology workers. However, neither the amount of industry R&D nor average weekly wage of high-tech workers were positively correlated with the number of high-technology workers.

This study provides additional quantitative evidence to complement the work of van Agtmael and Bakker. While van Agtmael and Bakker provide several examples of how universities can stimulate growth in high-technology industry, which in turn can revitalize the economies of Rust Belt cities, they provide no statistical evidence for their claims. Through quantitative analysis, this study will determine whether van Agtmael and Bakker's claims hold statistical significance. Although both Gittell et al. and Riddel and Schwer use regression analysis to determine the economic impact of high-technology industry, they fail to include university outputs in their models. Additionally, neither Gittell et al. nor Riddel and Schwer focus on Rust Belt cities specifically, in contrast to this study.

Economic Impact of Higher Education

The endogenous growth model of Romer claims that human capital accumulation determines the rate of economic growth. As part of his emphasis on human capital accumulation, Romer argues that when human capital is invested in R&D activities, the returns on R&D will lead to higher rates of economic growth, as his model exhibits increasing returns to scale for research. Yet at equilibrium, too little human capital is devoted to research, so Romer calls for policies that will encourage research and increase the amount of human capital. By this standard, the Romer model suggests that improvements in human capital, such as a greater quantity of well-educated college students, increases in R&D expenditures, and increases in the number of patents should generate higher rates of economic growth.

Mindful of the endogenous growth model, economists have conducted a large amount of research to determine the impact universities have on economic growth in their local communities. Goldstein et al. (1995) claim that a university has eight different functions to promote economic development, the creation of knowledge, human-capital creation, transfer of existing know-how, technological innovation, capital investment, regional leadership, knowledge infrastructure production, and influence on the region.

Lendel (2010) uses regression analysis to determine the impact American universities have on the economies of their respective metropolitan area economies. Lendel argues that universities stimulate regional economic growth through university outputs, including education, contracted research, trained labor, technology diffusion, new knowledge, new products and industries, and cultural products. Based on the output of multiple regression models, Lendel finds that the presence of research universities has a significantly positive impact on their respective regional economies. Additionally, the presence of universities that conduct R&D in high-technology fields is positively associated with the region's ability to sustain economic growth and employment, even in periods of economic downturn. Also, while having prestigious universities does enable strong economic growth, Lendel's findings show that a university's R&D expenditures and ability to generate a skilled labor force matter even more for sustaining a regional economy. Furthermore, Lendel discovers that a strong culture of entrepreneurship, measured by the number of start-up companies, supports knowledge spillovers from universities. Ultimately, Lendel claims that these university outputs help lead to a rise in employment during periods of economic expansion and help sustain employment levels during economic downturns.

Kantor and Whalley (2014) evaluate the significance of the local knowledge spillover benefits of research universities. They estimate that a 1% increase in university research expenditures in a county increases local labor income in other sectors by 0.08%. Kantor and Whalley also claim that spillover benefits will be greater when local universities focus on research and are connected to local firms in technological terms. However, university spillover benefits do not befall each county equally, as firms that are technologically close to local universities receive a spillover benefit double that of the typical firm that is not technologically close. For example, in an area with a strong pharmaceutical cluster and universities that specialize in pharmaceuticals, pharmaceutical firms will receive double the spillover benefit of a non-pharmaceutical firm. Kantor and Whalley also find evidence that the local economy may see an increase in spillover benefits in the long run, as the composition of local firms may conform to the university's specialties in order to match the university's knowledge spillovers.

Goldstein and Renault (2004) use a quasi-experimental approach to test five different hypotheses regarding the impact of universities on regional economic development. First, Goldstein and Renault find evidence that research universities significantly contributed to regional economic development from 1986-1998, but not from 1969-1986. Second, their data indicates that a university's technological innovation, in the form of university patents, did not have a significant impact on regional economic development. Third, Goldstein and Renault determine that from 1986-1998, MSA's with a top research university economically outperformed MSA's without a top research university. This finding matches the finding of Lendel that having prestigious universities, especially ones with significant research expenditures, enables strong economic growth. Goldstein and Renault do not find enough evidence to determine whether a research university or economic business cluster was more important to the success of a local economy. Likewise, they do not find evidence that a research university could serve as a substitute for a business cluster. Lastly, while Goldstein and Renault discover evidence that the scale of university R&D activity significantly increases the average wage in an MSA, they stress that the strength of the relationship is modest.

Beeson and Montgomery (1993) examine the role colleges and universities play in local labor markets in different MSA's. Their analysis finds that MSA employment growth rates are positively associated with changes in university R&D funding as well as with the number of prestigious science and engineering programs at local universities. In addition, there is a positive relationship between the percentage of workers employed as scientists and engineers and both R&D funding levels and the percentage of bachelor's degrees awarded in science and engineering.

Link and Scott (2007) argue that universities can also support regional economic development through the development of university research parks (URP's). Link and Scott note that there are several economic benefits of URP's, including their ability to transfer knowledge from academic research, produce knowledge spillovers, and catalyze national and regional economic growth. Link and Scott argue that URP's enable demand and supply forces to generate related economic clusters. From a demand perspective, they argue that when a firm locates to a URP, they can minimize their search costs. From a supply perspective, Link and Scott claim that a URP provides firms access to highly-skilled labor in the forms of graduate students and consulting faculty. Regarding the regional economic development impact of URP's, Link and Scott cite the work of Goldstein and Luger (1990). Specifically, Goldstein and Luger found that the potential economic development impacts of URP's include the location of R&D activity, R&D firm spin-offs, location of new manufacturing services and attendant supply-chain services, and increased firm productivity.

I build off this literature by focusing on the Rust Belt region as well as by focusing on the way universities support their local economy through high-technology industry. The research of Lendel supports this study as it indicates the impact of university outputs on the regional economy, in all parts of the United States. However, Lendel does not look specifically at mid-sized Rust Belt cities, but at the United States as a whole. The research of Kantor and Whalley, Goldstein and Renault, Beeson and Montgomery, and Link and Scott likewise do not focus on the Rust Belt specifically. Furthermore, few of these studies detail the role of high-technology industry in terms of economic development. Although Kantor and Whalley do consider the relevance of technological clusters and knowledge spillovers in their model, their focus is on the impact universities have on local wages in other economic sectors. While Beeson and Montgomery focus on employment in high-technology fields, they fail to account for changes in overall employment levels as the result of changes in university outputs. In contrast, this study seeks to determine the impact university outputs have specifically on high-technology industry, and how this relationship generates overall economic spillover benefits.

Impact of Higher Education on High-Technology Industry

Anselin, Varga, and Acs (1997) study the impact university R&D expenditures have on their local regions ability to innovate, both directly and indirectly through their interaction with private sector R&D. Based on their regression output, Anselin et al. find that university R&D had a significantly positive impact on knowledge innovation in a university's respective MSA and state.

Like Anselin et al., Fallah, Partridge, and Rickman (2014) look at the role universities play in generating knowledge spillovers in their local areas. Fallah et al. find that the presence of research universities within 160 kilometers of an MSA does not significantly impact that MSA's high technology employment growth. However, Fallah et al. do find that universities are an important source of human capital, as having a higher share of university-educated workers positively relates to high-technology industry growth in a given MSA.

Woodward, Figueiredo, and Guimarães (2006) examine the impact that academic research conducted by universities in science and engineering has on attracting high-technology industry to each university's respective locality. Using a Dirichlet-Multinomial regression model that controls for labor, land, taxes, and other factors, Woodward et al. estimate that an additional $1 million in university R&D expenditures increase the odds of attracting high-technology industry to a university's locality by only 0.26%. Furthermore, Woodward et al. find that university R&D expenditures yielded spillover benefits within a 145 miles radius from the centroid of the county where the university is located, but no farther. They also discover that university R&D activity better attracts high-technology industry to counties where R&D spending is below the median level among all counties (Woodward et al., 2006).

This study will expand upon this literature by focusing on the impact that university outputs have on high-technology employment and wage levels. While Anselin et al. and Woodward et al. study how universities can stimulate growth in local high-technology industry, they focus innovation and business growth respectively. And although Fallah et al. study the impact of universities on high-technology employment growth, they fail to examine the impact on high-technology wage level. Furthermore, this study will see whether these university outputs also have a significant impact on the overall economy, not just high-technology industry. And none of these studies focus on Rust Belt cities as this study does.

The role of this paper in the literature

This study examines the role of universities in Rust Belt cities, as described by van Agtmael and Bakker. Specifically, I assess the impact of universities in Rust Belt cities on local high-technology industry. To confirm the spillover benefits of these university outputs beyond high-technology industry, I examine whether these university outputs have a positive effect on the overall economy of a Rust Belt city. This study therefore serves as a linkage between the literature on higher education's impact on the local economy and the literature on higher education's impact on high-technology industry. While there is some research on the impact higher education has on local high-technology industry, that research fails to examine the impact of higher education on high-technology employment and wage levels. Additionally, the existing research does not consider the economic spillover benefits of university outputs beyond high-technology industry, which this study does consider. As van Agtmael and Bakker note, serious investments in high-technology industry can yield economic spillover benefits that support other parts of the local economy. Additionally, both Gittell et al. and Riddel and Schwer find that improvements in a locality's high technology industry can in turn improve local job growth and innovation. Lastly, the existing literature on the impact of universities on high-technology industry and on the local economy fails to specifically examine the case of the Rust Belt.

This paper focuses on mid-sized Rust Belt cities because of their unique economic situations. Hobor (2012) excludes large cities from his analysis of Rust Belt deindustrialization because mid-sized cities were smaller, more isolated centers of production that were heavily dependent of manufacturing for economic success. Recognizing the difference between large and mid-sized cities, van Agtmael and Bakker detail how mid-sized Rust Belt cities in the United States and in Europe have sought to improve their high-technology industries as a way to improve their city's economic situation. Many of these cities turn to their local universities as a partner in supporting their local high-technology industry, much like how Albany, New York depends on the presence of the SUNY Poly College of Nanoscale Science and Engineering to support its business cluster for semiconductors. However, van Agtmael and Bakker fail to provide any statistical support for their argument. And while other pieces of literature provide statistical evidence that universities either support local high-technology industry or local economic growth, they fail to show a statistical linkage between the impact university's influence on high-technology industry has on local economic growth. Considering the work of van Agtmael and Bakker, I search for any statistically significant links between the various university outputs and the employment and the average wage levels in the high-technology industries of Rust Belt cities. Additionally, I will determine if there are significant spillover benefits by examining the relationship between these university outputs and the overall employment and average wage levels in Rust Belt cities. If a statistically significant link between university support for local high-technology industry and local economic growth can be shown, this study can better inform the economic development strategies of mid-sized Rust Belt cities.

Methodology

Data Collection

The regression models featured in this research depend on a variety of data representing different variables and coming from different sources. The data spans from 2000 to 2015 and is collected on an annual basis. The timeframe from 2000 to 2015 captures two different periods of economic expansion in the United States, from 2001 to 2007 and from 2009 to the present. During this time, industry in the Rust Belt began to transform such that high-technology industry became relatively more dominant in local Rust Belt economies. Traditional manufacturing in the Rust Belt began to fold under the pressure of outside competitors during this time period as well. As Alder et al. note, employment levels and wage levels in Rust Belt manufacturing hit all-time lows in 2000. By studying the period from 2000 to 2015, I can account for the change in the economy of the Rust Belt marked by the rise of high-technology industry and the decline of traditional industries that had dominated the region for decades.

The data cover 26 different cities and 25 different Metropolitan Statistical Areas (MSA's), which are listed in Table 9.[1] These cities are all mid-sized with a population between 100,000 and 300,000 in 2015.[2] These cities are in the following states: Connecticut, Illinois, Indiana, Massachusetts, Michigan, New York, Ohio, Pennsylvania, and Rhode Island. Illinois, Indiana, Michigan, New York, Ohio, and Pennsylvania all are regarded today as traditional Rust Belt states. Connecticut, Massachusetts, and Rhode Island, although not often regarded as part of the Rust Belt, each share an industrial background similar to their neighbors to the west. Indeed, the New England cities included have struggled with deindustrialization and the loss of traditional manufacturing. For example, Lowell, Massachusetts was founded because of local industrial activity and was regarded as the textile manufacturing center of America until the mid-20th century, when the local textile industry collapsed. And if one walked the streets of some mid-sized New England cities like Bridgeport, Connecticut and saw its closed factories and abandoned warehouses, he or she could draw parallels between Bridgeport and economically

[1] The MSA's used are defined by the Bureau of Labor Statistics (BLS) in 2015. The BLS changed MSA definitions and names changed slightly from 2000 to 2015, mostly between 2004 and 2005.

[2] Cities that were suburbs of a larger nearby city, or in other words were part of the MSA of a major city, were not included in this study. This study follows the example of Hobor, which excludes suburbs of major cities as the economies of the suburbs are largely dependent on the major urban center. Rather, this study seeks to focus on mid-sized cities that have economies which are independent and not tied to a different, larger urban center. So, while Cambridge, Massachusetts is a mid-sized city that, in terms of population, would fit the criteria needed for this study, as an extension of Boston it is inappropriate to include in this study.

struggling mid-sized cities in the Midwest. The selection of these states is inspired in part by Hobor. As Hobor (2012) notes, all these states are connected "by Interstate 90 in what was once a regional, metals-based, production system consisting of the automobile, electronics, primary metals, fabricated metals, and machinery industries" (p. 418). Map 1 shows how each of these Rust Belt cities in the Midwest and New England are connected on an east-west axis.

For each one of the 26 cities chosen, select local universities capture the university impact on local high-technology industry. These universities are all located within 20 miles of the geographically central zip code of each city and are included in the Department of Education's College Scorecard database. Furthermore, each one of these universities is a public or private, non-profit, 4-year university. Community colleges, junior colleges, and for-profit institutions were not included. Table 12 includes the list of universities used for each city.

University Variables

To measure the impact of universities on local high-technology industries, I use the following variables: the number of undergraduate students in STEM fields, the number of undergraduate students in non-STEM fields, the number of graduate students in STEM fields, the natural logarithm of the amount of university R&D expenditures in STEM fields, and the number of university patents. Each one of these variables capture different university outputs. The variables for the number of undergraduate students and the number of graduate students capture the human capital output of universities. Improvements in the number of university students, who will later graduate from the university, improve human capital in the form of skilled labor. The variable for university R&D expenditures directly measures the economic impact of R&D activities. University R&D activities enable technological innovation, attract relevant businesses, and employ research professionals. Data on university R&D expenditures comes from the National Science Foundation's (2017) (NSF) Survey of Research and Development Expenditures at Universities and Colleges and Higher Education Research and Development Survey.

The number of undergraduate students enrolled at local institutions, both in STEM fields and in non-STEM fields, captures the human capital impact of universities. Not only does Romer view human capital accumulation as key for continued economic growth, but the findings of Fallah et al. indicate that the share of university-educated workers positively relates to high-technology growth. Data for the number of undergraduate students comes from the U.S. Department of Education's (2018) College Scorecard database, which provides the number of undergraduate students enrolled in each institution of higher education in the United States per academic year. In addition, the College Scorecard database breaks down the student population by academic major, allowing for the calculation of the number of undergraduates in STEM fields.[3] For each city the study uses the sum of undergraduate students, both as a whole and in STEM fields only, enrolled in every 4-year, non-profit university within a 20-mile radius of the city.[4] The variables for the number of undergraduate students, both in STEM fields and not in STEM fields, are lagged to adjust for the fact that these students will not enter the workforce until after they graduate. Therefore, the primary human capital benefit of the number of undergraduate students will not be completely felt until at least a year after the given year when some of the students are in the labor force.

[3] For the purpose of this study, STEM majors include the following CIP (Classification of Instructional Programs) codes as established by the U.S. Department of Education's National Center for Education Statistics (NCES): CIP 11- Computer and Information Sciences and Support Services, CIP 14- Engineering, CIP 26- Biological and Biomedical Sciences, CIP 27- Mathematics and Statistics, and CIP 40- Physical Sciences.
[4] These undergraduate student estimates are based on the author's calculations.

Like the variable for the number of undergraduate students, the variable for the number of graduate students in STEM fields also captures a local university's ability to improve human capital and provide skilled labor. Graduate students are typically more involved in research projects than their undergraduate peers, and therefore represent a more skilled source of labor than undergraduate students. Both Link and Scott and van Agtmael and Bakker note that graduate students serve as a form of highly-skilled labor that works with both faculty and local industry on R&D projects. The data on the number of graduate students comes from the NSF's (2018) Annual Survey of Graduate Students & Postdoctorates in Science and Engineering. For each city, I use the sum of all graduate students in science and engineering fields enrolled in a non-profit postgraduate university within a 20-mile radius of the city. The graduate student variable is lagged for a single year to adjust for the fact that graduate students will not enter the workforce until they complete their graduate studies.

The variable for university R&D expenditures captures the amount of scientific research local universities produce in a given year. This variable is adjusted for inflation and is measured in terms of 2015 $US. As Kantor and Whalley find, university research expenditures produce economic spillover benefits, including an increase in wages and support for technological innovation within local firms, especially when those firms specialize in the same fields as local universities. Furthermore, Romer uses his endogenous growth model to argue that increased investments in R&D activities will lead to higher rates of economic growth. Data on university R&D expenditures in STEM fields comes from the NSF (2017) Survey of Research and Development Expenditures at Universities and Colleges for the years 2000 to 2009 and the NSF Higher Education Research and Development Survey from 2010 to 2015.[5] This study uses the

[5] The NSF replaced the Survey of Research and Development Expenditures at Universities and Colleges with the NSF Higher Education Research and Development Survey starting in 2010.

natural logarithm of R&D expenditures to account for wide variation in university R&D expenditures between cities. Indeed, variation is large such that the standard deviation of R&D expenditures is larger than the average value for R&D expenditures, as seen in the summary statistics table, Table 10. For while some universities, like those located in Evansville, Indiana, do not conduct significant amounts of R&D, other universities like the University of Michigan in Ann Arbor conduct over a billion dollars' worth of R&D alone per year. As a result, the natural logarithm of university R&D expenditures better explains the impact that R&D expenditures have on the different dependent variables.[6] Since R&D expenditures have immediate economic benefits, such as employing professional researchers, this variable is not lagged.

The number of university patents captures the amount of technical innovation produced by local universities. One concept of university patents is that they produce economic spillovers as they can be used to generate innovative activities. On one hand, Riddel and Schwer lend credence to these spillover benefits, as they found that a 1% increase in the number of patents correlates to a 1.12% increase in the number of high-technology workers. However, Goldstein and Renault (2004) found that the number of university patents had no significant impact on regional economic development. The NSF directly provided data on the patents issued to American universities up to 2016.[7][8] This patent variable is double lagged to capture the fact that

[6] The variables for R&D expenditures, per capita income, the average wage, and the average high-technology wage are all in 2015 $US to adjust for inflation.

[7] A representative from the U.S. Patent and Trademark Office directly emailed me a file containing information on all the patents issued to American universities from 1971 to 2016. In the bibliography, this is referred to as "U.S. Patent and Trademark Office. (2017, February 22). US Colleges and Universities 1969-2016. Unpublished raw data."

[8] While Link and Scott find that there are several economic benefits of University Research Parks, this study does not include a variable for University Research Parks in the regression models. A few factors went into this decision. First, there is no publicly available database of university research parks that includes every university research park in the United States. To properly account for the number of university research parks, I would therefore either need to exclude some university research parks or create a list of university research parks using data from multiple sources. Using multiple sources to capture the number of research parks creates another problem, however, as different sources use different definitions of what a university research park is. Second, out of the databases that are publicly available, none of them account for the size and scope of the research park. Because there is neither a

it can take multiple years after a patent is issued to successfully create a start-up company based on that patent.

Control Variables

To control for variation in size between the cities, I use the natural logarithm of city population. Using the natural logarithm accounts for the wide variation in city population, as while some cities have just over 100,000 residents in a given year, others have a population of about 300,000 residents. The control variable for city population is especially important for the regression models with the employment dependent variable. Cities with larger populations will have higher levels of employment, as they will have a larger labor force. Data on city population came from U.S. Census Bureau estimates.

To control for the differences in standards of living by city, I include the per capita personal income level in 2015 $US for each city's MSA. In the regressions with the average wage dependent variable, the per capita income control variable captures the differences in standard of living. Assuming per capita income is an appropriate measure of standard of living, I assume that cities with higher levels of per capita income will have higher average wage levels. And for the regressions with employment dependent variables, the per capita income variable should control for the concept that wealthier cities are more likely to have higher rates of employment. Assuming the city population control variable accounts for the role of population size, including the per capita income variable accounts for the concept that if there are two cities

database that fully captures every university research park nor a database that measures the scope and size of University Research Parks, I do not include the University Research Park variable, as I would not have confidence in the variable's accuracy.

of equivalent size, employment will be higher in the wealthier city. Per capita personal income data comes Federal Reserve Economic Data (2017) estimates.

The state corporate income tax rate, controls for the impact that corporate income taxes have on local businesses. Economic theory suggests that higher state corporate tax rates should discourage business activity in a state, as firms may look to lower tax states to operate in. For the employment and wage regressions, the state corporate tax rate variable controls for the theory that a higher tax rate will discourage business investment and could lead to lower levels of employment and wages. Data on state corporate tax rates comes from the Tax Foundation (2015) and the Tax Foundation (2013).

Lastly, I include a year variable to account for variation that can be explained as a part of a time trend. For example, I would generally expect that wages would rise over time as the standard of living improves.

Dependent Variables

I use four different dependent variables to measure the impact of the university variables. Specifically, I use the natural logarithm of the employment level in high-technology industry in an MSA, the natural logarithm of the overall employment level in an MSA, the average wage for all high-tech workers in an MSA, and the average wage for all workers in an MSA.[9]

The natural logarithm of high-technology industry employment measures the impact university outputs have on employment in high-technology industry for Rust Belt cities.[10] If the

[9] All data for these four variables come from the Bureau of Labor Statistics' (BLS) Occupational Employment Statistics (OES) program. The reason the variables all use MSA- level data, not at city-level data, is because the BLS does not collect annual wage and employment on a city level for the OES program. So, while city-level data would admittedly be ideal for this analysis, MSA-level data was the most relevant data available.
[10] High-technology industry occupations are determined by the BLS. This paper follows the example of Wolf and Terrell, which identifies high-technology occupations as those held by STEM workers. Specifically, high-technology occupations are defined as those in sub-domain 1 of the 2010 SOC occupations included in STEM. Sub-

university variables have a positively significant value, then the regression output would indicate that university outputs have a positive impact on high-technology employment, and therefore on local high-technology industry.

The natural logarithm of overall employment measures the impact that the various university outputs have on employment in a Rust Belt city and its surrounding area. The regression on the natural logarithm of employment variable captures the overall economic impact university outputs have on a Rust Belt city. Namely, if university variables have a significantly positive value, then the regression output would indicate that university outputs have a positive impact on employment.

These two variables are in natural logarithm form to account for the wide variation in employment. Like the city population variable, there is a wide variation in the labor force size in each city's MSA, as larger cities have more workers. Using the natural logarithm of employment, both overall and just in high-technology industry, allows the regression model to better capture the impact the different experimental variables have on employment.

The regressions for the average wage level in high-technology industry for a given MSA and the overall average wage level each measure the impact university outputs have on wage levels in a Rust Belt city and its surrounding area. The variable for the average wage level in high-technology occupations captures the impact university outputs have on wages in high-technology industry. If the coefficients for the university variables are significantly positive, then the regression output would indicate that university outputs have a positive impact on wage levels in high-technology industry. The variable for the overall average wage level in an MSA

domain 1 occupations are specifically "Life and Physical Science, Engineering, Mathematics, and Information Technology Occupations." Specific examples of high-technology occupations include Computer Programmers (SOC Code 15-1131), Industrial Engineers (SOC Code 17-2112), and Chemists (SOC Code 19-2031) among others.

captures the impact that university variables have on the average wage level in an MSA for all occupations. If the university variables are significantly positive, then the regression output would indicate that university outputs have a positive impact on wage levels.[11]

However, there is a possibility that an increase in employment that results from improvements in the university variables can negate any significant wage increases. For example, if an increase in one of the university variables increases the number of workers available in a Rust Belt city, one could expect the supply of labor to rise as a result. If the university variables attract investment to the Rust Belt city such that businesses wish to hire additional workers, then one could expect the demand for labor to rise as a well. The combination of increasing demand and supply for labor would, as Graph 1 indicates, increase employment from “Emp” to “Emp’”. However, the change an increase in both the demand and supply for labor has an ambiguous change on wage levels. Depending on the size of the increases in demand and supply for labor, wages could rise, drop, or remain constant as a result. If the increase in labor demand exceeds the increase in labor supply, wage levels ought to increase. If the increase in labor supply exceeds the increase in labor demand, wage levels ought to decrease. If the increase in labor size is equivalent to the increase in labor demand, wage levels will remain constant.

Research Design

Different Types of Regression Models Used

To measure the economic impact of university STEM outputs, I use three different types of regression models. I use an ordinary least squares (OLS) model with robust standard errors, an

[11] A table of the summary statistics of these dependent variables, as well as of the various independent variables, can be found in Table 10.

OLS model with robust standard errors clustered by each city, and a city fixed effects model. The OLS model with robust standard errors accounts for heteroscedasticity and provides a general basis for the economic impact of the various university outputs. The OLS model with clustered robust standard errors accounts for a given city's observations not being truly independent of one another. Specifically, using robust standard errors clustered by city accounts for the concept that the error terms for observations belonging to the same city are likely correlated with each other. Since I use panel-level data, a clustered robust standard model adjusts for correlation between data belonging to the same city but in different years.

The city fixed effects regression model accounts for variation between the different cities used in the regression model. Unlike the random effects models, the fixed effects model assumes that the city-specific effects are correlated with unobserved independent variables which could lead to an omitted variable bias. The fixed effects model removes the unobserved variation across cities that remains constant over time, such that the model only uses variation within a city over time to determine the coefficients of the different independent variables. The fixed effects model works best, however, if there is more variation within cities as opposed to between cities.

I use four different types of regression models for this study. For each regression model, the equation follows the format:

$$(Dependent\ Variable)_{i,t} = \beta_0 + \beta_1(GRAD)_{i,t-1} + \beta_2(STEM)_{i,t-1} + \beta_3(Non-STEM)_{i,t-1} + \beta_4(ln(RD))_{i,t} + \beta_5(PAT)_{i,t-1} + \beta_6(PAT)_{i,t-2} + \beta_7(ln(POP))_{i,t} + \beta_8(PCI) + \beta_9(SCT)_{i,t} + \beta_{10}(YEAR) + \varepsilon_{i,t}.$$ [12][13]

[12] In the models, each variable is described in terms of city *i* and year *t*.
[13] The independent variables can be identified as *GRAD* = number of graduate students in STEM fields in terms of thousands of students, *STEM* = number of undergraduate students in STEM Fields in terms of thousands of students, *NON-STEM* = number of undergraduate students in non-STEM fields in terms of thousands of students, *RD* =

Each model has a unique dependent variable. The first model's dependent variable is the natural logarithm of employment, $(ln(HTEMP))_{i,t}$. The second model's dependent variable is the natural logarithm of overall employment, $(ln(EMP))_{i,t}$. The third model's dependent variable is the average high-technology wage, $(HTWAGE)_{i,t}$. The fourth model's dependent variable is the average overall wage, $(WAGE)_{i,t}$.

As mentioned previously, I include lags on the variables for the number of undergraduate students in STEM fields, the number of undergraduate students not in STEM fields, the number of graduate students in STEM fields, and the number of university patents. I use lags for each one of these variables because the impact of each variable on the various dependent variables should not occur at that given year. The number of students, both undergraduate and graduate, will not significantly impact employment or wage levels until they enter the labor force. Assuming most of these students graduate, these students will not enter the labor force for at least another year. And the primary benefit of university patents, startup companies, typically take years to form after a patent is issued.

Additionally, using lags helps with causal interpretation of the regression results. Specifically, using lags supports, but does not confirm, the hypothesis that changes in the different university variables may cause a change in the different dependent variables. As one can understand how observations from the previous year will cause changes in a dependent variable from the current year. However, one would not as easily understand how data from the current year causes changes in a variable from the previous year.

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university R&D expenditures in science and engineering in millions of 2015 $US, *PAT* = number of patents issued to local universities, *POP* = city population, *PCI* = per capita income, *SCT* = state corporate income tax rate, and *YEAR* = year. The notation *ln(RD)* and *ln(POP)* refer to the natural logarithm of *RD* and natural logarithm of *POP* respectively.

Stratified Regional Models

While I include both cities from the Midwest and New England using the standard of Hobor, I would be remiss to not account for regional differences. To account for any regional differences, I separate the regression models by region. In the stratified regression models, one group of cities are from the New England region while another group of cities are from the Midwest.[14] I expect that the coefficients for the Midwestern cities will be different from those in New England for several reasons. One difference is that the cities in the New England region are relatively close to each other in geographic terms. For example, Bridgeport, Connecticut and Stamford, Connecticut are so close to each other that they belong to the same MSA. In the Midwest, however, the cities studied are geographically farther apart from each other and never in the same MSA. Furthermore, the New England region has, on average, a relatively higher standard of living than the Midwest.

Another reason I include the stratified models is to separate for the relative impact larger metropolitan areas have on mid-sized Rust Belt cities regarding high-technology industry development. In New England, both Boston and New York City are large clusters for high-technology industry.[15] As a result, skilled labor, in the form of college graduates and, to a lesser degree, university researchers, from New England Rust Belt cities will more likely look to Boston and New York City for employment in high-technology industry. The Midwest, on the other hand, lacks major cities that have developed high-technology clusters as large as those of

[14] States from the Midwest include Indiana, Illinois, Michigan, New York, Ohio, and Pennsylvania. States from New England include Connecticut, Massachusetts, and Rhode Island. The Midwest includes New York as all the cities from New York in this study are from the upstate New York/Great Lakes region. As a result, these New York cities are geographically and economically more similar to their peer cities in the Midwest than their peer cities in New England.

[15] The real estate services firm Cushman & Wakefield (2017), as part of its list of the top 25 technology clusters in the United States, rank Boston and New York City as the 4th and 15th best technology clusters. In contrast, the only Midwestern cities in this list are Chicago and Columbus, which are the 16th and 19th best technology clusters respectively.

Boston or New York. Combined with the relatively greater distances between cities in the Midwest, I expect that the possibility of large metropolitan areas attracting skilled labor away from mid-sized Rust Belt cities to be higher in New England than in the Midwest.

And on average, the cities measured in New England have relatively greater amounts of undergraduate students, graduate students, university R&D expenditures, and university patents than their Midwestern peers, as seen in Table 11. Such findings reflect the fact that the cities of New England have, relative to those of the Midwest, a better educated population and a higher standard of living. Due to these and other potentially unobserved regional differences, I use stratified regression models to both better describe the relationships between university outputs and the dependent variables as well as to adjust for the influence of regional differences on the regression output.

This study does not include a stratified fixed effects regression model. The fixed effects model adjusts for variation between the cities of the model. By stratifying the regressions by region, I separate the Midwestern cities from the New England cities, and thereby remove much of the variation between cities as that variation is likely largely driven by regional differences. Additionally, with the reduced sample sizes in the stratified regressions there is too little within-city variation to precisely estimate a fixed effects model.

Regression Output

High-Technology and Overall Employment

Table 1 shows the regression output for the *ln(HTEMP)* dependent variable. Table 2 shows the regression output for the *ln(EMP)* dependent variable. The control variables act as one would assume in both the *ln(HTEMP)* and *ln(EMP)* regressions. Particularly, the model finds that an increase in *PCI* is positively associated with an increase in both *ln(HTEMP)* and *ln(EMP)* at the 1% significance level. Additionally, every model finds a significantly positive relationship between *ln(POP)* and employment. And in the regressions with robust standard error for both *ln(HTEMP)* and *ln(EMP)*, *SCT* has a significantly negative relationship with employment.

Some of the university variables do not have as significant an impact on employment. For the regressions with the *ln(HTEMP)* dependent variable, *GRAD* is not statistically significant in the clustered robust standard error and the fixed effects regression models. *NON-STEM* is also statistically insignificant in the robust standard error regression model with clustered standard errors. In the robust standard error regression model, both variables are negatively and significantly associated with *ln(HTEMP*). A similar pattern emerges in the regressions with the *ln(EMP)* dependent variable.

The double lagged *PAT* variable is negatively associated with *ln(HTEMP)* in all three different regression models. In the robust standard error model, the variable is statistically insignificant. In the robust standard error model with clustered standard errors, the first lag is significant at the 10% level while the second lag is significant at the 5% level. In the regressions with the *ln(EMP)* dependent variable, *PAT* is statistically insignificant in each lag and in each model. The relative statistical insignificance of *PAT* mirrors the finding of Goldstein and Renault (2004) that university patents do not significantly impact regional economic development. However, the statistical insignificance of *PAT* contradicts Riddel and Schwer who found that an increase in patents correlates to an increase in high-technology employment.

The *ln(RD)* variable is only statistically significant in the robust standard error model with the *ln(HTEMP)*, in which a 1% increase in *RD*, in terms of millions of 2015 $US, is associated with a 0.0520% increase in high-technology employment growth. While the R&D

expenditures variable is statistically insignificant in the two other regression models, it still has a positive value. The same pattern emerges in the regressions for the *ln(EMP)* dependent variable. While the coefficient for *ln(RD)* is positive in all models, *ln(RD)* is only statistically significant in the robust standard error model. In the robust standard error mode, a 1% increase in university R&D expenditures is associated with a 0.0649% increase in overall employment growth. The positive relationship between *ln(RD)* and *ln(EMP)* in the robust standard error regression output supports the finding of Lendel that universities that conduct R&D in high-technology fields are positively associated with regional employment.

In the robust standard error model and the robust standard error model with clustered standard errors, a one standard deviation increase in *STEM* is significantly associated with a 0.637 increase in *ln*(*HTEMP*), or an 89.0% increase in *HTEMP*.[16][17] This lagged variable is significant at the 1% level and 5% level for the robust standard error model and the robust standard error model with clustered standard errors respectively. A similar pattern emerges in the regressions with the *ln(EMP)* dependent variable. In all three models, the relationship between *STEM* and *ln(EMP)* is positive. In the robust standard error and fixed effects models, the relationship between *STEM* and *ln(EMP)* is significant at the 1% and 10% level respectively. For the sake of comparison with the coefficient of *STEM* in the robust standard error regression with the *ln(HTEMP)* dependent variable, a one standard deviation increase in *STEM* is associated with a 0.287 increase in *ln(EMP)*, or a 33.3% increase in *EMP*.

[16] I use standard deviations to measure the impact of *STEM* and other university variables not in logarithmic form on the dependent variables to provide a standardized way to measure each university variable's relative impact on the various dependent variables. The respective standard deviations for each university variable can be found in Tables 10 and 11, which contain the overall and stratified summary statistics respectively.

[17] I calculate a 0.637 increase in *ln(HTEMP)* as: $0.299 * 2.13 = 0.637$, or $(coefficient\ of\ STEM) * (standard\ deviation\ of\ STEM) = impact\ of\ STEM\ on\ \ln(HTEMP)\ in\ terms\ of\ standard\ deviations$. I calculate an 89.0% increase in *HTEMP* as: $(e^{0.637} - 1) * 100\% = 89.0\%$. These calculations can be applied to other estimates in terms of standard deviations.

Most notable in the regressions for both the *ln(HTEMP)* and *ln(EMP)* dependent variables is the relative insignificance of the university variables in the fixed effects regression model. *GRAD*, *NON-STEM*, *ln(RD)*, and second lag of *PAT* are all statistically insignificant in the fixed effects model for *ln(HTEMP)* and *ln(EMP)*. In the fixed effect model for *ln(HTEMP)*, only the first lag of the university patent variable is statistically significant, as it has a negative value at the 10% level. In the fixed effects model for *ln(EMP)*, only *STEM* is statistically significant, albeit at the 10% level.

Examining this employment-based output, the most statistically significant and economically significant variable appears to be *STEM*. Not only is it significantly positive in the robust standard error model for the *ln(HTEMP)* regression, but it is also significantly positive in the clustered robust standard error model. And in the regressions for the *ln(EMP*) dependent variable, *STEM* is significantly positive in the robust standard error and fixed effects model. While the *ln(RD)* is the only other university variable that has a consistently positive coefficient in all models, this variable is only statistically significant in the robust standard error models. Since *ln(RD)* is statistically insignificant in the clustered robust standard error and fixed effects regression models, it is unclear that increases in *ln(RD)* are associated with higher levels of employment. The significance of *ln(RD)* is explored further in the stratified regression model output.

Average Wage of High-Technology Workers and of All Workers

Table 3 shows the regression output for the *HTWAGE* dependent variable. Table 4 shows the regression output for the *WAGE* dependent variable. In the robust standard error model, the clustered robust standard error model, and the fixed effects model for *HTWAGE*, *PCI* is positively associated with the average high-technology wage as expected. In the robust standard error model and the clustered robust standard error model, the coefficients are significant at the 1% level. In the fixed effects model the coefficient is significant at the 5% level. Likewise, each one of the regression models for the *WAGE* dependent variables find a significantly positive relationship between *PCI* and *WAGE*.

Inconsistent coefficient values across the different models makes it hard to determine which university outputs, if any, have a significant impact on the *HTWAGE* and *WAGE* variables. For example, *GRAD* is statistically significant at the 1% level in both the robust standard error model and in the fixed effects model of the regressions with the *HTWAGE* dependent variable. In the robust standard error model, a one standard deviation increase in *GRAD* is associated with a $1,740.20 decrease in *HTWAGE*. In the fixed effects model, a one standard deviation increase in *GRAD* is associated with a $2,601.50 decrease in *HTWAGE*. In the clustered robust standard error model, the variable is statistically insignificant. In the regressions for the *WAGE* dependent variable, however, *GRAD* is positively associated with *WAGE* in all three models. The only significantly positive relationship between *GRAD* and *WAGE* is in the robust standard error model, a one standard deviation increase in *GRAD* is associated with a $574.80 increase in *WAGE*. This positive relationship is notable for its contrast to the negative relationship between *GRAD* and *HTWAGE*.

For the regressions with the *HTWAGE* dependent variable, *ln(RD)* is only statistically significant in the robust standard error model. In this model, the coefficient is significant at the 1% level and a 1% increase in *RD* is associated with a $13.71 increase in the average high-technology wage. However, *ln(RD)* is statistically insignificant in the clustered robust standard errors model and in the fixed effects model. While the coefficient of *ln(RD)* is positive in the regressions with the *WAGE* dependent variable, *ln(RD)* is statistically insignificant in all models.

Also, in the regressions with the *HTWAGE* dependent variable, the robust standard error model finds that a one standard deviation increase in *STEM* is positively associated with a $1356.10 increase in *HTWAGE*. Yet while this coefficient is statistically significant at the 1% level in the robust standard error model, it is statistically insignificant in the clustered robust standard error model. In the fixed effects model, the coefficient is statistically insignificant and negative. Likewise, in the robust standard error regression with the *WAGE* dependent variable, the relationship between *STEM* and *WAGE* is significantly positive. But the relationship between *STEM* and *WAGE* is statistically insignificant in the clustered robust standard error and fixed effects models.

The regression output does not clearly indicate which university outputs consistently correlate to a significant increase in the average wage level of a Rust Belt city, both in high-technology industry and for the entire local economy. The regression output does suggest that *ln(RD)* may be significantly and positively related with *HTWAGE*. Yet since the relationship between *ln(RD)* and *WAGE* is insignificant, I cannot confirm the findings of Kantor and Whalley that an increase in university R&D expenditures increases wages in other economic sectors. And although *STEM* is positively associated with *HTWAGE* and *WAGE*, the positive relationship is only statistically significant in the robust standard error model. None of the other university variables have a consistently positive relationship with *HTWAGE* or *WAGE*.

Regression Output for Stratified Models

I include stratified regression models in this study to separate regional differences that distinguish the Midwest from New England. Additionally, incorporating stratified regression models helps us better understand whether the regression output for all Rust Belt cities best describes the economic impact of university outputs in both the Midwest and New England. The overall regression output indicates that increases in high-technology employment and overall employment are associated with increases in the number of undergraduate students in STEM fields and, to a lesser degree, increases in university R&D expenditures. In terms of the average high-technology wage and average overall wage dependent variables, there is some evidence that improvements in the number of STEM undergraduates and in R&D expenditures can correlate with an increase in wage levels. The stratified regression output reveals that the output for Midwestern cities mirrors the overall output much more than the output for New England cities.

High-Technology and Overall Employment

The stratified regression output reveals significant differences between the impact the various university variables have on *ln(HTEMP)* and *ln(EMP)* in New England Rust Belt cities and in Midwestern Rust Belt cities. For example, Table 5 shows that while *GRAD* is negatively associated with *ln(HTEMP)* for Midwestern cities, *GRAD* is positively associated with *ln(HTEMP)* for New England cities. In both regression groups, the variables are significant at the 1% level for the robust standard error models, yet statistically insignificant in the model with clustered robust standard errors. In the stratified regressions with the *ln(EMP)* dependent variable, as shown in Table 6, the coefficient of *GRAD* is significantly negative for Midwestern cities while positive for New England cities, but only significant in the robust standard error model.

In the stratified regressions for the *ln(HTEMP)* dependent variable, the coefficient of both lags of *PAT* in the regression of Midwestern cities is negative while both lags are positive in the regression of New England cities. The same pattern occurs in the stratified regressions for the *ln(EMP)* dependent variable.

NON-STEM is the only variable in the stratified regression models with the *ln(HTEMP)* dependent variable that has the same sign in both groups. In both the Midwestern and New England city groups, an increase in *NON-STEM* undergraduates is associated with a decrease in *ln(HTEMP)*. This variable is statistically significant at the 1% level in the robust standard error model in both the Midwestern and New England city groups, yet statistically insignificant in the clustered robust standard error models for both groups. In the stratified regression models with the *ln(EMP)* variable, all the coefficients of *NON-STEM* are negative as well.

In the regressions with the *ln(HTEMP)* dependent variable and with the *ln(EMP)* dependent variable, the variable for *ln(RD)* is statistically significant in nearly every case. For Midwestern cities, a 1% increase in *RD* is associated with a 0.144% increase in *HTEMP*. This coefficient is significant at the 1% level in the robust standard error model yet statistically insignificant in the clustered robust standard error model. For New England cities, a 1% increase in *RD* is associated with a 0.665% decrease in *HTEMP*. This coefficient is significant at the 1% level in the robust standard error model and significant at the 10% level in the clustered robust standard error model. A similar pattern emerges in the regressions with the *ln(EMP)* dependent variable. In these regressions, an increase in *ln(RD)* is significantly associated with an increase in *ln(EMP)* for Midwestern cities. And like in the stratified regressions with the *ln(HTEMP)* dependent variable, an increase in *ln(RD)* is significantly associated with a decrease in *ln(EMP)* for New England cities.

Another interesting contrast is that *STEM* is positive in the regression models for Midwestern cities, yet negative in the regression models for New England cities. For Midwestern cities, an increase in *STEM* is related with a significant increase in *ln(HTEMP)* and in *ln(EMP)* in both regression models. For New England cities, an increase in STEM is correlated with a significant decrease in *ln(HTEMP)* and in *ln(EMP)* in both regression models.

Average Wage of High-Technology Workers and of All Workers

As it is in the stratified regression output for *ln(HTEMP)* and *ln(EMP)*, the regression output for the Midwestern cities group is very dissimilar from that of the New England cities group in the stratified regressions for *HTWAGE* and *WAGE*. The stratified output for *HTWAGE* and *WAGE* are in Table 7 and Table 8 respectively. Of the control variables, only the variable for per capita income is consistent across all models. In the group of Midwestern cities and in the group of New England cities, *PCI* is positively associated with a significant increase in *HTWAGE* and *WAGE* at the 1% level.

Among the university variables, only the *NON-STEM* lagged variable is consistent across all models. In each regression model an increase in *NON-STEM* is significantly associated with a decrease in *HTWAGE* and in *WAGE*.

PAT does not have much of a significant impact on *HTWAGE* in the stratified models. The only instance in which *PAT* is significant is the first lag in the New England cities models. In this case, an increase in *PAT* is negatively associated with the *HTWAGE*. This relationship is significant at the 5% level in the robust standard error model and in the clustered robust standard error model. *PAT* does not have much of a significant impact on *WAGE* as well.

GRAD consistently has a negative relationship with the *HTWAGE* across both regression types and groups of cities. However, *GRAD* is statistically significant only in the robust standard error regression output for Midwestern cities. In this model, a one standard deviation increase in *GRAD* is associated with a $2,037.99 decrease in the average high-technology wage at the 1% significance level. Interestingly enough, *GRAD* has a consistently positive relationship with *WAGE* across both regression types and group of cities. Furthermore, all these relationships are statistically and economically significant.

For New England cities, *ln(RD)* has a positive yet statistically insignificant impact on the *HTWAGE*. For Midwestern cities, however, *ln(RD)* has a significantly positive impact on the *HTWAGE*. A 1% increase in *RD* is associated with a $14.78 increase in *HTWAGE* for Midwestern cities. This coefficient is significant at the 1% level in the robust standard error model and at the 10% level in the clustered robust standard error model. In the stratified regression models for the *WAGE* dependent variable, the *ln(RD)* variables have the opposite effect that they have in the stratified regression models for the *HTWAGE* dependent variable. For New England cities, *ln(RD)* is significantly negative related with *WAGE*. And for Midwestern cities, *ln(RD)* is positively associated with *WAGE*, but this relationship is statistically insignificant.

The relationship between the *STEM* and *HTWAGE* is statistically insignificant and negative in the stratified regression models for the group of Midwestern cities. However, the relationship between these two variables is significantly positive for the group of New England cities. In this group, a one standard deviation increase in *STEM* is associated with a $1,918.94

increase in *HTWAGE*. This coefficient is significant at the 1% level in the robust standard error model and at the 10% level in the clustered robust standard error model. In the regressions with the *WAGE* dependent variable, *STEM* is statistically insignificant in both the Midwestern and New England cities groups.

Analysis of Regression Output

Several of the university variables have a consistent impact, or lack thereof, on the employment and wage dependent variables in the regression models with all the cities included. In nearly every regression model, the lags for the *PAT* variable are statistically insignificant. And in the cases where *PAT* is statistically significant, such as the stratified regression models for *ln(EMP)*, *PAT* has a slightly negative impact on *ln(EMP)*. Like *PAT, NON-STEM* is insignificant across most of the regression models. In the normal regression models for *ln(HTEMP)*, *ln(EMP), HTWAGE,* and *WAGE, NON-STEM* is statistically insignificant in nearly every model. And while *NON-STEM* is statistically significant in the stratified regressions for *HTWAGE* and *WAGE*, *NON-STEM* has a negative coefficient in each case. As a result, the regression output indicates that *PAT* and *NON-STEM* do not have a positively significant impact on employment and wage levels in the Rust Belt.

GRAD generally does not have a significantly positive impact on the various dependent variables. The one exception is for the regressions for *WAGE*. In the robust standard error regression model with the *WAGE* dependent variable, *GRAD* has a positive relationship with *WAGE* at the 10% statistical significance level. While *GRAD* is positively associated with *WAGE* in the clustered robust standard error and fixed effects models, however, this relationship is not statistically significant. Even if *GRAD* is associated with an increase in *WAGE*, however, *GRAD* does not have a significantly positive relationship with *HTWAGE*. As a result, the regression output does not support the hypothesis that an increase in *GRAD* would support *HTWAGE* and *WAGE*.

ln(RD) has a significantly positive impact on *ln(HTEMP)*, *ln(EMP)*, and *HTWAGE* in the robust standard error regression models. Yet while *ln(RD)* has a positive value on *ln(HTEMP)*, *ln(EMP)*, and *HTWAGE* in the clustered robust standard error and fixed effects models, the relationships between *ln(RD)* and these three dependent variables are statistically insignificant.

STEM appears to have one of the most consistently positive impacts of all the university variables. In the robust standard error and clustered robust standard error models, *STEM* is found to be positively associated with *ln(HTEMP)*. Likewise, *STEM* is positively and significantly associated with *ln(EMP)* in the robust standard error and fixed effects models. In both the cases of *STEM's* association with *ln*(*HTEMP)* and its association with ln(*EMP)*, the coefficient of *STEM* is economically significant as well. However, there is less evidence to suggest that *STEM* improves wage levels. For in the regressions for *HTWAGE* and *WAGE*, *STEM* is only significantly positive in the robust standard error regressions.

The stratified regression models reveal that while the output of the Midwestern cities largely mirrors that of the overall output, the output of the New England cities greatly contrasts form the overall regression model. Such results confirm the positive impact some of the university variables have on employment and wage levels in the Midwestern Rust Belt. However, the stratified results indicate that other factors beyond the university explain the economic situation of New England Rust Belt cities and of their high-technology industries.

For example, the stratified regression models indicate that *PAT* does not have a significantly positive impact on any of the dependent variables for the Midwestern cities group, mirroring the normal regression output. However, in the New England cities group the second lag of *PAT* is positively and significantly associated with *ln(HTEMP)* and *ln(EMP)* in both the robust standard error and clustered robust standard error models. Such a result suggests that, for New England cities, an increase in the number of university patents is associated with an increase in high-technology and overall employment.

GRAD has a similar impact on the various dependent variables in the stratified regression models for the Midwestern cities group as it does in the normal regression models. *GRAD* is only positively associated with *WAGE* in the robust standard error and clustered robust standard error regression models, mirroring the normal regression output. Likewise, *GRAD* has a positively significant relationship with *WAGE* in the robust standard error and clustered robust standard error regression models for the New England cities group. However, in both the Midwestern cities group and New England cities group, the relationship between *GRAD* and *HTWAGE* is consistently negative. In addition, *GRAD* also has a significantly positive relationship with *ln(HTEMP)* and *ln(EMP)* in the stratified robust standard error regression models for New England cities. As a result, there is some evidence that an increase in the number of graduate students may correlate with an increase employment levels for New England cities.

The stratified regression models confirm that *ln(RD)* has a significantly positive impact on *ln(HTEMP)*, *ln(EMP)*, and *HTWAGE* in the robust standard error and clustered robust standard error model, but only for Midwestern cities. For the New England cities, *ln(RD)* is either significantly negative or both positive and statistically insignificant. Graph 2 and Graph 3 highlight the relationship between *ln(RD)* and *ln(HTEMP)* and between *ln(RD)* and *ln(EMP)* respectively. In Graphs 2 and 3, the variation within cities primarily drives the positive relationships between *ln(RD)* and *ln(HTEMP)* and between *ln(RD)* and *ln(EMP)* for Midwestern cities.

STEM has a significantly positive impact on *ln(HTEMP)* and *ln(EMP)* in both the stratified robust standard error and clustered robust standard error regression models for Midwestern cities, much like the overall regression output. However, the output for the New England cities group reveals a stark contrast. In the New England cities group, an increase in *STEM* is significantly associated with a decrease in both *ln(HTEMP)* and in *ln(EMP)*. Graph 4 and Graph 5 highlight the relationship between *STEM* and *ln(HTEMP)* and between *STEM* and *ln(EMP)* respectively. In Graph 4 and Graph 5, the negative relationships between *STEM* and *ln(HTEMP)* and between *STEM* and *ln(EMP)* for New England are driven largely by variation across cities, as within different cities there is no consistent positive or negative relationship. Within different Midwestern cities, however, there are positive relationships between *STEM* and *ln(HTEMP)* and between *STEM* and *ln(EMP)*.

And on a more minor note, in both the stratified robust standard error and clustered robust standard error regression models, an increase in *STEM* for New England cities is significantly and positively associated with an increase in *HTWAGE*.

In sum, the regression output indicates that *GRAD*, *ln(RD)*, and *STEM* consistently have the most significantly positive impact on the various economic measures. Increases in *GRAD* correlate to an increase in *WAGE*, but not to an increase in *HTWAGE*. And for New England cities, *GRAD* has a significantly positive relationship with *ln(HTEMP)* and *ln(EMP)*. *ln(RD)* has a significantly positive relationship with *ln(HTEMP)*, *ln(EMP)*, and *WAGE*, but this relationship only appears to be true for Midwestern cities. *STEM* has a significantly positive relationship with *ln(HTEMP)* and *ln(EMP)*, but like *ln(RD)*, only for Midwestern cities. *STEM* also has a significantly positive relationship with *HTWAGE* for New England cities only. While *STEM* may not improve *ln(HTEMP)* and *ln(EMP)* for New England cities, however, *PAT* has a significantly positive relationship with these employment variables. The significantly positive relationships between *ln(RD)* and *ln(HTEMP)* as well as between *STEM* and *ln(HTEMP)* are consistent with the hypothesis of Beeson and Montgomery that increases in the number of undergraduates in science and engineering and in R&D funding are positively associated with increases in the number of employed scientists and engineers.

While none of the university variables are associated with an increase both *HTWAGE* and *WAGE* in either the overall or stratified models, such a finding follows the economic logic of an increase in labor demand and labor supply. As mentioned earlier and explained in Graph 1, an increase in both the demand for labor and supply for labor will increase employment levels but will have an ambiguous effect on wage levels. As a result, any changes in wage levels that result from an increase in labor demand and supply could likely be statistically insignificant. That the regression output finds that none of the university variables are significantly and positively associated with *HTWAGE* and *WAGE* therefore makes sense. For according to the model for the labor market, improvements in employment need not necessarily significantly change wage levels.

Interpreting the Causality of the Results

The research design supports, but does not necessarily prove, the concept that the relationship between the independent variables and the dependent variables may be causal. As mentioned previously in the paper, each one of the university variables, except *ln(RD)*, has at least one lag. As a result, the regression uses data from the previous year when including lagged variables in the regression model.[18]

The use of lags supports the claim that changes in the independent variables cause changes in the dependent variables. Since the lagged variables use the prior year's data, changes in the university outputs occur before changes in the employment and wage variables. As a result, it makes sense that changes in the university variables from the past year can cause changes in the employment and wage variables from the present year.

There are a few limitations to this interpretation of the regression output. From a research design standpoint, I cannot conclude with complete certainty that changes in the university variables cause changes in the employment and wage variables. A third variable could be causing changes in both the university variables and the employment and wage dependent variables, representing a "third variable problem" or a case of confounding. However, I attempted to control for any confounding with the *ln(POP)* and *PCI* control variables. Specifically, the presence of *ln(POP)* controls for the possibility that any relationship is actually driven by an unaccounted variable for city population. The presence of *PCI* controls for the possibility that any relationship is actually driven by an unaccounted variable for standard of living. As a result, I doubt that there is an unaccounted "third variable" that is the true source of any causality.

Another potential limitation is the possibility of omitted variable bias. While the R^2 of the regression models are generally high, there is still much unexplained variation in the models. Like confounding, omitting an important variable could bias the relationships of the university variables and the dependent variables. Omitted variable bias could result in an overestimation or

[18] Since *PAT* is double lagged, the regression models use patent data from the previous year and the year before that.

underestimation of the relationship between an independent and dependent variable. This regression model likely has some omitted variable bias as there are variables that cannot be quantified which influence the relationship between the university variables and the dependent variables. Since these variables cannot be quantified, they are therefore not accounted for in the regression models. For example, Goldstein et al. (1995) cite “regional leadership” as a key way in which universities drive economic development in their respective communities. Sadly, there is no great way to quantify leadership, so I cannot include a measure for a university’s leadership ability in the regression models. However, I do not believe that these omitted variables significantly bias the results of the regressions, especially in regards to the direction of the relationships. In particular, the fixed effects regressions control for any omitted variables that remain constant over time for a given city.

One specific concern with this model lies in the relationship between the control and dependent variables and the impact they have on the size of the coefficients for the university variables. For example, *PCI*, meant to control for differences in the standard of living by city, is correlated with *HTWAGE* and *WAGE* with an R^2 of 0.5814 and 0.6786 respectively.[19] Likewise, *ln(POP)*, meant to control for differences in city size, is correlated with *ln(HETMP)* and *ln(EMP)* with an R^2 of 0.6164 and 0.4292 respectively.[20] Due to such correlation, the presence of *PCI* in the regressions for *HTWAGE* and *WAGE* could potentially lead us to underestimate the true impact of the different university variables on both *HTWAGE* and *WAGE*. If *PCI* controls for variation in *HTWAGE* and *WAGE* that may have been driven by a specific university variable, the coefficient for that university variable will be lower than its true impact. Likewise, there is a chance that the presence of *ln(POP)* leads us to underestimate the true impact of the

[19] R^2 estimates based on the author’s calculations.
[20] R^2 estimates based on the author’s calculations.

different university variables on both *ln(HTEMP)* and *ln(EMP)*. Even though such correlation could lead to an underestimate of the size of the impact of the university variables, I include *PCI* and *ln(POP)* to reduce the likelihood of confounding.

Case Studies

Brief Overview of Case Studies Used

Two cities used in this study are further examined to provide a qualitative understanding of the quantitative analysis. These cities are Akron, Ohio and Springfield, Massachusetts. These case studies are meant to provide detailed explanations as to how different cities and their universities sought to improve their local economies and high-technology industries between 2000 and 2015.

I use Akron and Springfield as case studies as they are each representative Rust Belt cities of the Midwest and of New England respectively. From 2000 to 2015, the average high-technology employment level, overall employment level, high-technology wage level, and overall wage level for Akron, Ohio is very similar to those of all Midwestern cities used in this study.[21] In addition to being economically representative, Akron fits the historical description of a Rust Belt city. As the case study will further review, Akron has suffered from the patterns of deindustrialization that define the Rust Belt. And Akron has several major universities within the Akron and in nearby communities, meaning it has sufficient levels of university outputs to examine the economic impact of its universities. I use Springfield as a case study for New England Rust Belt cities for reasons that are similar to those for using Akron as a case study for

[21] Akron MSA: average high-technology employment = 15,249, average employment= 320,544, average high-technology wage = $72,733, average overall wage = $44,303. All Midwestern MSA's used in this study: average high-technology employment = 14,718, average employment= 321,944, average high-technology wage = $72,562, average overall wage = $44,861. Averages are based on BLS data from 2000 to 2015 and the author's calculations.

Midwestern Rust Belt cities. Namely, Springfield is economically representative of a Rust Belt city in New England with its history of strong industry and deindustrialization. Additionally, there are several universities located in the city of Springfield and in nearby communities. Together, Akron and Springfield highlight the role universities play in encouraging growth in local high-technology industry for Rust Belt cities.

Akron, Ohio

Policy experts and researchers have touted Akron as a leading city in the movement to transition from a Rust Belt economy to an economy focused in high-technology industry. Akron is called the "Rubber Capital of the World" due to its historic cluster of rubber-product manufacturers. Ledebur and Taylor (2008) note that, at one time, four of the country's five largest tire companies, B.F. Goodrich, Goodyear, Firestone, and General Tire, were based in Akron. Akron also served as a major railroad hub between New York City and Chicago, which allowed the city to store the region's grains in silos that belonged to the Quaker Oats company (van Agtmael & Bakker, p. 95). However, towards the end of the 20th century, Akron's tire companies lost to overseas competition and began to outsource much of their supply chain from Akron to foreign countries like Mexico and China (van Agtmael & Bakker, p. 95-96). By 2000, foreign companies had bought out most of Akron's tire manufacturers, tire manufacturing plants had closed, the grain silos stood empty, and the city no longer served as a railroad hub (van Agtmael & Bakker, p. 96; The University of Akron, 2011).

In the 21st century, however, universities in Akron have taken steps to improve their STEM education programs with the hope that such investments would help the Akron economy transition towards high-technology industry. For example, Akron's local universities have not just grown in terms of undergraduate student population but have increased in terms of the number of undergraduate students in STEM fields. In 2000, 45,335 undergraduate students attended a non-profit 4-year university in the Akron area.[22] By 2015, that figure rose by 32.8% to 60,199. At the same time, the percentage of undergraduate students in STEM fields outgrew the growth rate of all undergraduate students. While about 9.3% of undergraduates majored in a STEM subject in 2000, 10.1% of Akron-area undergraduates majored in a STEM subject in 2015. Akron's growth in higher education and in the number of undergraduates in STEM fields mirrors that of other Rust Belt cities. Of the Midwestern universities used in this study, the percentage of undergraduate students in STEM fields on average rose from 13.5% in 2000 to 16.9% in 2015.

One reason for the increase in the number of STEM undergraduate students at Akron-area universities is the presence of state government incentives. Akron-area universities like the University of Akron and Kent State University have partnered with the Ohio Department of Education to encourage more students to study in STEM fields with the Choose Ohio First scholarship, which provides financial aid to select recipients that study in STEM fields (University of Akron, 2018). In its 2014-2015 annual report, the Ohio Department of Higher Education (2016) found that students in the Choose Ohio First program were more likely to graduate than students not in the Choose Ohio First program. Additionally, the Ohio Department of Education cites a 65% increase in the number of STEM degrees awarded from 2007 to 2015 as a sign of the success of the Choose Ohio First program. Other states have similar scholarships, such as New York, which offers a full-time scholarship to a SUNY university for the top 10% of students from a New York high school's graduating class provided they study in a STEM field as

[22] Estimate comes from the author's calculations using College Scorecard Data from the U.S. Department of Education (2018).

part of the NYS STEM Incentive Program (New York State Higher Education Services Corporation, 2018).

The Choose Ohio First program represents the most significant investment that Ohio has made in STEM higher education. When announced in 2008, then-Governor Ted Strickland claimed that the Choose Ohio First program was designed “to attract and retain students in the vital areas of science and technology,” as investing in Ohioans is most “crucial” to the economic success of the state (Chaney, 2008). Instead of applying one strategy to the entire state, however, Choose Ohio First gave resources to the different universities of each region such that each region could pursue its own path. For example, Kent State University led the “Integrated Science Training for Northeast Ohio’s Future Biomedical and Biotechnology Workforce” initiative, which was funded through the Choose Ohio First program. This initiative was designed to attract 580 STEM students over 5 years that could work in the different health care institutions of the Northeast Ohio region, which includes Akron (Chaney, 2008). That the Choose Ohio First program could support different regions of Ohio differently ensures that not only does each part of Ohio benefit from the program, but that universities can better make the investments needed to improve their respective local and regional economies.

The number of graduate students in STEM fields at Akron-area universities grew by 73% from 1,549 in 2000 to 2,682 in 2015. The University of Akron and Kent State University are the only two local institutions that have graduate students in STEM fields and they each saw increases of 677 graduate students and 751 graduate students respectively from 2000 to 2015. Many of those who graduate with Ph.D.’s in polymer science are hired upon graduation as research scientists by large, local companies that specialize in polymers, which allow these companies to further innovate and remain competitive (Braunerhjelm, Carlsson, Cetindamar, &

Johansson 2000, p. 487). As a result, Akron-area universities provide a source of skilled labor to the Akron economy through its graduate students.

The number of graduate students rose in large part because both the University of Akron and Kent State University committed themselves to significant levels of scientific R&D, especially in polymers. In the early 2000's, both the University of Akron and Kent State University understood that Akron's tradition as the "Rubber Capital" meant that the region had a labor force knowledgeable in the materials used to make tires, specifically rubber, synthetics, and steel (van Agtmael & Bakker, 100). As such, both universities expanded their research in high-tech polymers that would match the needs of local businesses in high-technology industries and help create a regional high-technology cluster. At the University of Akron, the College of Engineering and the College of Polymer Science and Engineering has the largest academic program dedicated to the study of polymers and acts as one of "the world's most important concentrations of polymer expertise" according to van Agtmael and Bakker. The University of Akron also helped found the Austen BioInnovation Institute in 2008 alongside regional health care systems and hospitals, which focuses on science research in biomaterials and orthopedics (The University of Akron). Meanwhile at Kent State University, the Glenn H. Brown Liquid Crystal Institute supports research in liquid crystal display (LDC).

The number of patents issued by the U.S. Patent and Trademark Office to local universities in Akron as a result of university R&D activities, generally rose from 2000 to 2015. Additionally, the research conducted by the University of Akron and Kent State University helped lead to the creation of spinoff companies. In 2012, the Austen BioInnovation Institute helped create Apto Orthopaedics, an orthopedic device company (Powell, 2012). Likewise, Akron Polymer Systems is a local startup company founded by two professors from the

University of Akron who licensed their research and hired 12 Ph.D. graduates and other scientists from the Akron area (van Agtmael & Bakker, p. 102).

Although not included in the regression model, university research parks are present in the Akron area. Kent State University is home to the Centennial Research Park, which the university acquired in 1997. According to Kent State University, the research park hosts two high-technology startup companies that are based in LCD research activities initially conducted at Kent State (Kent State University, 2018). The presence of two companies based in LCD research matches Kent State's background in the area, as seen with its Liquid Crystal Institute. The largest tenant at Centennial Research Park is the FlexMatters Accelerator, which Kent State describes as "a broad, public-private high-technology collaboration, designed to produce the next generation of advanced materials and promote regional economic development." (Kent State University)

The increases in both high-technology employment and high-technology wage levels in Akron highlight the city's growing high-technology industry. The number of high-technology workers in the Akron MSA grew by 21.0% from 2005 to 2015. This increase in high-technology employment exceeds the growth rate of overall employment in Akron, which decreased during this time. Additionally, the increase in high-technology employment mirrors the average increase in high-technology employment for Midwestern Rust Belt cities, which was 23.6% from 2005 to 2015. In addition, the percentage of Akron workers in high-technology industries rose from 4.4% in 2005 to 5.4% in 2015. On the other hand, the average high-technology wage showed inconsistent growth over time in Akron, as in 2015 $US, the average wage of a high-technology worker grew by 3.3% from 2005 to 2015. In contrast, the average high-technology wage for mid-sized Midwestern cities rose by 6.7% during that time period.

Springfield, Massachusetts

Like Akron, Springfield, Massachusetts has a proud industrial legacy and an economy that has suffered from deindustrialization and economic decline. Springfield's industrial legacy goes back to the earliest days of the United States, when George Washington established the first National Armory for the United States, the Springfield Armory, in 1777. Because of the Springfield Armory, traditional industrial manufacturing grew in Springfield for much of the 19th and early 20th centuries. Gun manufacturers like Smith & Wesson came into existence in 19th century Springfield, and technological innovations like interchangeable parts got their beginnings in Springfield. Until the 1970's, manufacturing prospered and drove economic growth in Springfield.

Starting in the 1970's, however, Springfield, along with much of New England, began to suffer from deindustrialization. From 1969 to 1976, 12% of job losses in all of Massachusetts were due to the closings of manufacturing plants (Forrant, 2007, p. 70). Things got worse for Springfield, as from 1980 to 2000, Hampden County, in which Springfield is a part of, lost about 43% of its industrial employment (Forrant, p. 70). And while Massachusetts as a whole managed to recover in the "Massachusetts Miracle" of the 1980's, most of the job growth that resulted from this "miracle" occurred in the Boston MSA (Forrant, p. 72). Springfield, located in the western part of the state away from Boston, did not witness any economic "miracle." At the start of the 21st century, the City of Springfield turned off streetlights and cut police, fire, and school jobs as a result of poor municipal finances (Forrant, p. 73). By 2004, the Massachusetts state government instituted a Financial Control Board which gave the state effective control over the city in return for a bailout for the city, as Springfield was running a $41 million deficit and owed the state about $50 million in back taxes (Plaisanace, 2009). Strong economic growth is still a priority for the city as it seeks to find its economic footing as it still reels from deindustrialization that began in the 1970's.

In recent years, Springfield has begun to make the investments needed to help it develop its high-technology industries and generate economic growth. At the university level, Springfield-area universities have been enrolling more and more students, especially in STEM fields. Both the total number of undergraduate students and the number of undergraduate students in STEM fields attending Springfield-area universities rose from 2000 to 2015, much like in Akron. The percentage of undergraduates in the Springfield area studying in STEM fields rose from 11.1% in 2000 to 16.8% in 2015. Local universities include some located directly in Springfield, such as Springfield College and American International College. Most, however, are located in communities outside of the city. The biggest concentration of universities is in Amherst where the University of Massachusetts Amherst, the flagship public university of Massachusetts, is located. Indeed, in the 2015-2016 academic year, 47.9% of all undergraduate students in the Springfield area came from the University of Massachusetts. At the University of Massachusetts specifically, the percentage of students majoring in STEM fields nearly doubled from 11.3% in 2000 to 21.1% in 2015 (U.S. Department of Education).

Smith College in Northampton, Massachusetts, has also made efforts to engage more of its students in STEM education. The all-girls college established the Clark Science Center in 1989, which seeks to support students and faculty in STEM fields. Later in 2007, faculty at Smith College created the AEMES (Achieving Excellence in Mathematics, Engineering and Science) program. The AEMES program aims to support students in STEM fields that come from backgrounds that are historically underrepresented in STEM fields (Smith College, 2018). Additionally, in 2015 Smith College provided 10 undergraduate students from low-income communities who sought to study in STEM fields full-cost scholarships as part of a program sponsored and funded by the Posse Foundation (Smith College, 2014).

The University of Massachusetts adopted initiatives meant to expand the number of graduate students it has in STEM fields as well. Like the initiatives at Smith College, the University of Massachusetts started initiatives meant to encourage students from underrepresented backgrounds to pursue a graduate education in STEM fields. For example, using a 1999 NSF grant, the University of Massachusetts founded the Northeast Alliance Program, which aims to enroll more students from underrepresented backgrounds, especially women and racial minorities, in Ph.D. programs (The Northeast Alliance Program at the University of Massachusetts Amherst, 2018). The Northeast Alliance Program in turn inspired the University of Massachusetts to create the STEM Diversity Institute, which aims to support students from underrepresented backgrounds as they pursue an education in STEM fields (The University of Massachusetts, 2018). The STEM Diversity Institute primarily focuses on graduate students, but also supports undergraduate students. Ultimately, these initiatives and others helped the University of Massachusetts increase the number of graduate students at the university and in the Springfield area. As a whole, the number of graduate students in the Springfield area grew by 96% from 2000 to 2015.

The increase in the number of undergraduate and graduate students in STEM fields matches one of the goals of the Massachusetts STEM Plan 2.0, issued by the Massachusetts STEM Advisory Council (2013) of former Governor Deval Patrick. Specifically, the STEM Advisory Council called for a 50% increase in “the percentage of students who complete STEM-related post-secondary degrees and certificates at public and private institutions” from 2008 to 2016 (Massachusetts STEM Advisory Council, 2013). Additionally, STEM Plan 2.0 advocated that STEM undergraduate and graduate degrees better match the needs of the “Massachusetts economy” (Massachusetts STEM Advisory Council, 2013). However, the plan does not target improvements in specific cities, such as its Rust Belt cities like Springfield.

The University of Massachusetts and other Springfield-area colleges have also increased R&D expenditures in STEM fields and expanded their R&D programs. In 2015, Amherst College, Hampshire College, Mount Holyoke College, Smith College, Western New England University, and the University of Massachusetts combined to spend over $209 million in STEM research activities. In contrast, their 2000 R&D expenditures numbered about $146 million in 2015 $US. The University of Massachusetts, also constructed a $165 million Life Science Laboratories facility, opening the facility in 2013 (Lederman, 2013). The facility was intended to improve research efforts in the life sciences at the university, attract and retain quality faculty, and create opportunities to collaborate with local businesses in the life sciences (Lederman). Many life science businesses are located across Massachusetts, primarily in the Boston area but also in the Springfield MSA to a lesser degree as well. Such research on the University of Massachusetts campus compliments the research at the Pioneer Valley Life Sciences Institute, which is a joint venture between the University of Massachusetts and Baystate Medical Center located in Springfield (Johnson, McGilpin, & Hanscom, 2013). The Pioneer Valley Life Sciences Institute allows the University of Massachusetts to conduct further research in life sciences, especially in areas related to health informatics and technology (Johnson et al.). The research in life sciences matches the economic needs of the Springfield area as healthcare plays a vital economic role in the region. The University of Massachusetts Donohue Institute Economic and Public Policy Research (2016) ranks the health services industry as the second largest business cluster in Springfield in terms of projected employment for which a bachelor’s degree is required. Considering the fact that much of the life sciences industry works closely with the health industry, research in the life science can help the Springfield region create a high-technology cluster oriented around health and life sciences.

Nearly every patent issued to a university in the Springfield area in recent years has been issued specifically to the University of Massachusetts Amherst. In 2015, for example, the University of Massachusetts Amherst received a total of 14 patents in chemical engineering, chemistry, food sciences, mechanical & industrial engineering, microbiology, and polymer science & engineering (Hayes, 2015). Half of the 2015 patents were in the life sciences, which matches the University of Massachusetts' interest in life sciences research (Hayes). From 1995 to 2015, the University of Massachusetts earned over $530 million from the technology transfer that resulted from the commercialization of university patents (The University of Massachusetts, 2015). Some of these patents have enabled researchers at the University of Massachusetts to create spin-off companies. However, most of these spin-off companies are not based in the City of Springfield itself. Of the 14 different start-up companies listed on the website of the University of Massachusetts Amherst's Technology Transfer Office, none of them are in Springfield itself (The University of Massachusetts Amherst). Therefore, none of these startup firms either promote a high-technology cluster in Springfield or revitalize the city's economy.

In contrast to Akron, there are no university research parks in Springfield. The closest thing to a university research park in the Springfield area is the Pioneer Valley Life Sciences Institute, which allows for collaborative research between the University of Massachusetts and Bay State Medical Center. However, this is not a true research park as the Pioneer Valley Life Sciences Institute does not host private businesses or encourage collaboration between the University of Massachusetts and private businesses.

The Springfield area has seen improvements in its high-technology industry in recent years. The number of high-technology workers rose by 12.3% from 2005 to 2015, although Springfield saw annual decreases in the number of high-technology workers in 2008 and 2009 during the Great Recession. In contrast, high-technology employment grew by only 5.9% for the average New England Rust Belt city used in this study during this same time period. However, the percentage of high-technology workers out of all workers in Springfield only increased marginally over time, from 3.5% in 2005 to 3.7% in 2015. The wage of high-technology workers in Springfield grew by 4.2% from 2005 to 2015. The growth of high-technology wages in Springfield exceeded that of all New England Rust Belt cities, which only grew by 2.8% during that same time period.

Overall economic improvements in Springfield mirror improvements in Springfield's high-technology industry, but to a lesser degree. Overall employment in the Springfield MSA grew by 6.5% from 2005 to 2015, half the rate of growth in high-technology employment during that time. And the average overall wage in the Springfield MSA rose by 4.5% from 2005 to 2015. Like the growth in employment, the growth rate of the average wage is less than that of the average high-technology wage for Springfield.

Akron and Springfield in Context

Both Akron and Springfield generated growth in high-technology industry, which in turned supported their overall economic activity. However, Akron more successfully generated growth in high-technology industry relative to Springfield, as high-technology employment growth in Akron outpaced that of Springfield. Akron's ability to succeed in ways that Springfield did not lies in part with the decision made by Akron universities to directly support high-technology industry and with the geographic particulars of the Midwest versus the Northeast.

One reason that Akron was more successful than Springfield in encouraging growth in high-technology industry is that the relationship between local universities and Akron is much closer than the relationship between local universities and Springfield. The University of Akron, located in the city of Akron, has a very close relationship with the city. In "The Akron Model" former University of Akron President Luis M. Proenza wrote that the University of Akron was dedicated to creating "a broad-based and robust platform for revitalizing the Northeast Ohio economy" (The University of Akron, 2011). In contrast, the University of Massachusetts has no clear policy focused on revitalizing the economy of the Springfield area.

The overall regression output and stratified regression output each offer quantitative evidence for the economic impact of university outputs in Rust Belt cities. One of the most significant ways to improve both high-technology employment levels and overall employment levels is to educate more undergraduates in STEM fields. In Akron, scholarships sponsored by the Ohio Department of Education lowered the cost of college for Ohio students in STEM fields. These scholarships may have incentivized studies in STEM fields and therefore educated more students that could work for local high-technology businesses. Additionally, these scholarships are awarded to students native to Ohio, educated in Ohio, and would likely remain in Ohio upon graduation for work. For the intent of the Choose Ohio First scholarship, according to the Ohio Department of Education, is to "bolster Ohio's economic strength by ensuring a ready workforce for STEMM-Related industries" (Ohio Department of Education, 2018). In Springfield, Smith College's approach to provide scholarships for undergraduate students that have historically been underrepresented in STEM fields could also expand the number of students in STEM fields.

However, the stratified regression output indicates that increasing the number of graduate students is associated with an increase in high-technology employment and overall employment for New England Rust Belt cities. An example of a program meant to increase the number of graduate students is the University of Massachusetts' STEM Diversity Institute, which is committed to encouraging underrepresented minorities and women to enter graduate studies STEM fields.

These commitments to encouraging undergraduate and graduate education in STEM fields partly explains why both Akron-area and Springfield-area universities saw the percentage increase in the number of undergraduate students in STEM fields exceed the percentage increase in the overall number of undergraduate students.[23]

Likewise, universities in both cities increased R&D expenditures quite significantly from 2000 to 2015. The University of Akron took advantage of Akron's business cluster in polymers to conduct high-technology polymer research. Likewise, Kent State University further advanced its research in LCD through its Liquid Crystal Institute. In both cases, the universities, their faculty, and students cooperated with local and national businesses to increase the amount of research, produce more patents, and, in some cases, tailor research needs to those of local businesses. And in the case of the University of Akron, many of the businesses that result from university research located in Akron itself.

In the Springfield area, the University of Massachusetts was responsible for most of the scientific research amongst local universities. However, whereas the University of Akron conducted most of its research within Akron itself, the University of Massachusetts conducted its research outside the city at its Amherst campus. And very few of the start-up companies that

[23] From 2000 to 2015, number of undergraduates in STEM fields at Akron-area universities rose by 45% while the number of total undergraduate students rose by 33%. In Springfield, those figures are 77% and 17% respectively.

result from research conducted at the University of Massachusetts locate to Springfield, but rather remain in Amherst or move to another part of New England (The University of Massachusetts Amherst).

While both Akron and Springfield both successfully cultivated high-technology industry, there is a noticeable difference in just how successful each city was. While high-technology employment in Akron grew by 21.0% from 2005 to 2015, high-technology employment in Springfield grew by 12.3% during that same time period. The fact that Akron grew its high-technology industry at a higher rate than Springfield did is especially interesting in light of the fact that Akron's population declined during that same time period.

One reason that Akron may have been more successful at encouraging growth in high-technology industry than Springfield, and one that is hard to quantify, is the relative presence of neighboring regions. For students studying at an Akron university, there are significant job opportunities in STEM fields in the Akron MSA. As mentioned earlier, Akron is home to large tire companies and other businesses with an interest in high-technology industry. And while students can travel to nearby Cleveland or Columbus for employment, there is still a significant business cluster in Akron in areas like advanced polymers. While universities in Springfield encourage study and research in STEM fields, their graduates can seek employment in other areas. For example, the real estate service business JLL (2017) ranks the Greater Boston Area as the top cluster for life sciences businesses. Graduates in life sciences from universities in the Springfield area will likely have more and better job opportunities in Boston and New York City where there are more businesses relevant to their field. While the University of Massachusetts can commit significant resources to life sciences research and education, Springfield may not directly reap the benefits of these investments. For researchers and graduates from Springfield-area universities will go to the life sciences cluster in Boston for research resources and employment. In contrast, JLL lists the Chicago Metro Area as the tenth best life science business cluster in the United States and as the only Midwestern city in their list of top 16 life sciences clusters. With their smaller clusters in area like life sciences, large cities in the Midwest like Chicago pose less of a threat to Akron in terms of attracting skilled labor than Boston poses to Springfield.

When examining the stratified regression output for example, both the number of undergraduate students in STEM fields and the amount of university R&D expenditures have a lesser impact on high-technology employment in New England than they do in the Midwest. In fact, the stratified regression output indicates that the relationship between STEM undergraduates and employment, as well as R&D and employment, is significantly negative. The presence of high-technology clusters in Boston and New York City with job opportunities in high-technology industry, can attract both undergraduate students and skilled researchers from universities located in the less affluent, smaller cities of New England such as Springfield.

Some of the differences in high-technology employment growth can also be explained by the different foci of programs meant to support high-technology growth in Ohio and Massachusetts respectively. While the Choose Ohio First program created initiatives tailored to the needs of different regions of Ohio, including the Akron region, the Massachusetts STEM Plan 2.0 did not tailor any initiatives towards the needs of any specific region. The Choose Ohio First initiative led by Kent State University specifically intended to educate 580 students in biology, chemistry, and physics such that these students could potentially work in the health care institutions of Northeast Ohio after they graduate (Chaney, 2008). In contrast, the Massachusetts STEM Plan 2.0 focused on promoting economic growth on a statewide level and lacked initiatives that could benefit a specific part of Massachusetts. Due to this focus on the overall economy of Massachusetts over that of Springfield specifically, Massachusetts policymakers enabled STEM students from the Springfield area to leave Springfield for other parts of Massachusetts, such as Boston, for employment.

While universities can encourage economic growth in their local cities through efforts to improve the local high-technology industry, the impact will be more significant the more directed the efforts. While Springfield and Akron benefited from university outputs, the fact that Akron's universities dedicated themselves to specifically supporting the Akron economy allowed Akron to benefit more from university outputs than Springfield did. For while Springfield has strong universities nearby, these universities do relatively less to directly support the Springfield economy. The University of Massachusetts, for example, keeps most of its research activities on its Amherst campus. And many of its students in STEM fields will be drawn towards larger high-technology clusters like the Boston MSA for future employment. As such, the dedication universities in the Rust Belt have to their local city and its economic welfare help determine how successfully university outputs support high-technology industry and the overall economy.

Conclusion

This study finds evidence suggesting that universities located in or near mid-sized Rust Belt cities can improve their community's economic situation by directly supporting the city's high-technology industry. Such findings support the claims made by van Agtmael and Bakker that university outputs can generate growth in local high-technology industry, which in turn can lead to economic spillover benefits.

The regression output reveals that certain university outputs can lead to economic benefits in both high-technology industry and in the overall Rust Belt economy. Increases in the number of undergraduate students in STEM fields and, to a lesser degree, in university R&D expenditures are strongly associated with increases in high-technology employment and in overall employment. However, these increases are more significant for Midwestern cities than for New England cities. Indeed, the stratified regression output suggests that Rust Belt cities in New England have a negative relationship between the number of STEM undergraduates and high-technology employment, as well as between the number of STEM undergraduates and overall employment. For New England cities, however the stratified regression output indicates that increases in the number of graduate students and in the number of university patents are associated with increases in high-technology employment and overall employment levels. The fact that these university outputs have a significantly positive effect on both high-technology employment and overall employment show that there are some economic spillover benefits, in terms of employment, from university outputs.

However, the regression output does not as clearly indicate the impact university outputs have on wage levels for Rust Belt cities. The overall regression output finds that no single university output consistently has a significantly positive impact on either the average high-technology wage level or the average overall wage level. While the stratified regression output indicates that higher university R&D expenditures are associated with an increase wages in high-technology occupations, they only do so for Midwestern cities. For New England cities, the number of undergraduate students in STEM fields is the only university output that has a significantly positive impact on high-technology wage levels. Neither of these variables have a significantly positive impact on overall wage levels in the stratified regression models, however.

And while the number of graduate students has a significantly positive relationship with the average overall wage level, the number of graduate students does not have a significantly positive relationship with the average high-technology wage level. As a result, improvements in the number of graduate spillovers do not improve high-technology industry wages which generate a spillover wage benefit to the entire economy. Since none of the variables have a consistently significantly positive relationship with the wage dependent variables, the regression output suggests that university outputs meant to support high-technology industry do not yield spillover benefits in regards to wage levels.

The case studies of Akron and Springfield, Massachusetts highlight ways universities can support growth in their local high-technology industries. Yet while the research activities of Akron-area universities directly engage the Akron community, especially local high-technology businesses, the research activities of the University of Massachusetts fail to directly engage the Springfield community. The University of Akron, for example, has worked with local businesses to improve its research activities. Additionally, the University of Akron's research has created spin-off companies that are based out of Akron and provide a further economic boon to the city. Also, graduating students from Akron-area universities can find jobs in local high-technology industries, which benefit the Akron area. At the University of Massachusetts, however, the research at the University of Massachusetts does not engage businesses from Springfield. The research at the University of Massachusetts best matches the life sciences cluster in the Greater Boston Area, away from Springfield. And while the University of Massachusetts does produce some spin-off companies, these companies do not reside in Springfield. And graduates of Springfield-area universities, especially those in STEM fields, will most likely leave the

Springfield area for larger metropolitan areas like Boston and New York City, where there are more job possibilities.

There is evidence that universities can help drive local economic growth in mid-sized Rust Belt cities by directly driving growth in their local high-technology industry, primarily through employment growth. Yet these findings best apply to the Rust Belt cities of the Midwest, and not so much to Rust Belt cities in New England. For the stratified regression output for the Midwestern cities group better matches the overall regression output than the stratified regression output for the New England cities group.

The output for New England cities group may differ from that of the Midwestern cities group because of the proximity of major high-technology clusters in Boston and New York. These two cities can draw both skilled labor in STEM fields away from the universities of mid-sized cities in New England as well as the spillover benefits of research in high-technology areas.

Further research can be conducted to tease out the New England anomaly. Namely, such research could explain why cities in New England, which have a similar industrial background as their Midwestern peers, have significant differences in the regression output. Such research can also explain how much of these differences can be explained by the proximity of high-technology hubs in Boston and New York. To definitively answer these questions, further research can expand the timeframe and add new variables such that more data points can improve the accuracy of the regression model.

Additional research could also examine the cases of Rust Belts in other countries, to determine whether the findings of this study hold in other cases beyond the American Rust Belt. For example, van Agtmael and Bakker discuss the Rust Belts of Europe in great detail, so this study’s framework could be applied to mid-sized Rust Belt cities in Europe as well.

This study suggests that the universities of mid-sized Rust Belt cities of the Midwest, and to a lesser degree, of mid-sized Rust Belt cities of New England, can drive local economic growth by making investments that benefit their respective high-technology industries. The two most significant university outputs for Midwestern cities are the number of undergraduate students in STEM fields and the amount of R&D expenditures in STEM fields. Increases in these two variables can lead to significant economic benefits for Midwestern Rust Belt cities in terms of increased levels of employment. The mid-sized Rust Belt cities of New England may need to adopt other approaches to stimulate economic growth, however. For larger high-technology hubs in the region, like Boston and New York City, will attract university graduates and university researchers away from the Rust Belt city. As a result, university investments in STEM education and R&D may not stimulate the growth in high-technology industry needed to revitalize the overall economy of a New England Rust Belt city.

Appendix

Table 1: Regression Results for the Natural Logarithm of High-Technology Employment at the MSA Level, 2000-2015

	Robust Standard Errors	Clustered Robust Standard Errors	Fixed Effects
Graduate Students in STEM fields$_{t-1}$ (in thousands)	-0.166*** (-3.47)	-0.166 (-1.30)	0.0286 (0.73)
Undergraduate Students in STEM fields$_{t-1}$ (in thousands)	0.299*** (8.59)	0.299** (2.59)	0.029 (1.17)
Undergraduate Students not in STEM fields$_{t-1}$ (in thousands)	-0.0117** (-2.46)	-0.0117 (-0.70)	-0.0028 (-0.52)
Natural Logarithm of R&D expenditures in Science and Engineering$_t$ (in millions of 2015 $US)	0.0520** (2.16)	0.0520 (0.75)	0.0202 (0.38)
Patents issued to a University$_{t-1}$	-0.00709 (-1.24)	-0.00709* (-1.95)	-0.00306* (-1.70)
Patents issued to a University$_{t-2}$	-0.00762 (-1.25)	-0.00762** (-2.38)	0.00019 (0.10)
Natural Log of City Population$_t$	0.774*** -6.58	0.774* -1.91	-0.578 (-1.19)
Per Capita Income (in 2015 $US)$_t$	0.0228*** (10.20)	0.0228*** (3.18)	0.0248*** (7.34)
Minimum State Corporate Income Tax$_t$	-0.0511*** (-4.60)	-0.0511 (-1.65)	-0.00519 (-0.78)
Year$_t$	0.00872 (1.19)	0.00872 (1.21)	0.00856** (2.38)
Constant$_t$	-18.74 (-1.29)	-18.74 (-1.38)	-2.191 (-0.23)
N	364	364	364
R^2	0.54	0.54	0.02

t-statistics are in parentheses
*: significant at 10% level, **: significant at 5% level, ***: significant at 1% level
Fixed Effects R^2 is the overall R^2
Data Sources include: Bureau of Labor Statistics (2018), National Science Foundation (2017), National Science Foundation (2018), Tax Foundation (2013), Tax Foundation (2015), U.S. Census Bureau (2016), U.S. Census Bureau (2017), U.S. Department of Education (2018), and U.S. Patent and Trademark Office (2017)
OLS estimates linear regression models

Table 2: Regression Results for the Natural Logarithm of Overall Employment at the MSA Level, 2000-2015

	Robust Standard Errors	Clustered Robust Standard Errors	Fixed Effects
Graduate Students in STEM fields$_{t-1}$ (in thousands)	-0.1740*** (-5.46)	-0.1740* (-1.90)	-0.0346 (-1.65)
Undergraduate Students in STEM fields$_{t-1}$ (in thousands)	0.1350*** (5.62)	0.1350 (1.67	0.0234* (1.77)
Undergraduate Students not in STEM fields$_{t-1}$ (in thousands)	0.00368 (1.11)	0.00368 (0.31)	-0.00323 (-1.13)
Natural Logarithm of R&D expenditures in Science and Engineering (in millions of 2015 $US)	0.0649*** (3.87)	0.0649 (1.3)	0.0252 (0.89)
Patents issued to a University$_{t-1}$	-0.00397 (-0.99)	-0.00397 (-1.68)	-0.00146 (-1.52)
Patents issued to a University$_{t-2}$	-0.00537 (-1.25)	-0.00537 (-1.69)	-0.000425 (-0.40)
Natural Log of City Population	0.825*** (10.16)	0.825*** (2.95)	0.877*** (3.39)
Per Capita Income (in 2015 $US)$_t$	0.0105*** (6.86)	0.0105** (2.22)	0.0252*** (14.03)
Minimum State Corporate Income Tax$_t$	-0.0214*** (-2.98)	-0.0214 (-1.09)	-0.00446 (-1.26)
Year$_t$	-0.00133 (-0.25)	-0.00133 (-0.27)	-0.00627** (-3.26)
Constant$_t$	4.506 (0.43)	4.506 (0.43)	13.40*** (2.67)
N	364	364	364
R^2	0.60	0.60	0.30

t-statistics are in parentheses
*: significant at 10% level, **: significant at 5% level, ***: significant at 1% level
Fixed Effects R^2 is the overall R^2
Data Sources include: Bureau of Labor Statistics (2018), National Science Foundation (2017), National Science Foundation (2018), Tax Foundation (2013), Tax Foundation (2015), U.S. Census Bureau (2016), U.S. Census Bureau (2017), U.S. Department of Education (2018), and U.S. Patent and Trademark Office (2017).
OLS estimates linear regression models

Table 3: Regression Results for the Average High-Technology Wage at the MSA Level, 2000-2015

	Robust Standard Errors	Clustered Robust Standard Errors	Fixed Effects
Graduate Students in STEM fields$_{t-1}$ (in thousands)	-1212.8*** (-2.66)	-1212.8 (-0.96)	-1813.1*** (-2.82)
Undergraduate Students in STEM fields$_{t-1}$ (in thousands)	636.7** (2.03)	636.7 (0.69)	-324.3 (-0.80)
Undergraduate Students not in STEM fields$_{t-1}$ (in thousands)	-85.47** (-2.51)	-85.5 (-0.87)	-264.8*** (-3.02)
Natural Logarithm of R&D expenditures in Science and Engineering$_t$ (in millions of 2015 $US)	1371.0*** (4.78)	1371.0 (1.65)	545.2 (0.63)
Patents issued to a University$_{t-1}$	-51.06 (-0.91)	-51.06 (-0.88)	-44.12 (-1.50)
Patents issued to a University$_{t-2}$	13.95 (0.24)	13.95 (0.25)	17.67 (0.55)
Natural Log of City Population$_t$	-2452.1** (-2.44)	-2452.1 (-0.80)	25761.3*** (3.26)
Per Capita Income (in 2015 $US)$_t$	415.6*** (17.66)	415.6*** (5.98)	123.2** (2.24)
Minimum State Corporate Income Tax$_t$	199.8* (1.82)	199.8 (0.66)	-396.1*** (-3.66)
Year$_t$	95.04 (1.4)	95.04 (1.01)	408.4*** (6.96)
Constant$_t$	-108245.6 (-0.79)	-108245.6 (-0.59)	-1043874.0*** (-6.80)
N	364	364	364
R^2	0.68	0.68	0.06

t-statistics are in parentheses
*: significant at 10% level, **: significant at 5% level, ***: significant at 1% level
Fixed Effects R^2 is the overall R^2
Data Sources include: Bureau of Labor Statistics (2018), National Science Foundation (2017), National Science Foundation (2018), Tax Foundation (2013), Tax Foundation (2015), U.S. Census Bureau (2016), U.S. Census Bureau (2017), U.S. Department of Education (2018), and U.S. Patent and Trademark Office (2017)
OLS estimates linear regression models

Table 4: Regression Results for the Average Overall Wage at the MSA Level, 2000-2015

	Robust Standard Errors	Clustered Robust Standard Errors	Fixed Effects
Graduate Students in STEM fields$_{t-1}$ (in thousands)	400.6* (1.70)	400.6 (0.65)	543.3 (1.44)
Undergraduate Students in STEM fields$_{t-1}$ (in thousands)	363.3** (2.03)	363.3 (0.67)	-214.3 (-0.90)
Undergraduate Students not in STEM fields$_{t-1}$ (in thousands)	-1.68 (-0.08)	-1.68 (-0.03)	-122.2** (-2.38)
Natural Logarithm of R&D expenditures in Science and Engineering$_t$ (in millions of 2015 $US)	117.3 (0.73)	117.3 (0.26)	446.5 (0.88)
Patents issued to a University$_{t-1}$	-2.168 (-0.09)	-2.168 (-0.09)	8.662 (0.50)
Patents issued to a University$_{t-2}$	5.652 (0.22)	5.652 (0.25)	9.684 (0.51)
Natural Log of City Population$_t$	-2686.0*** (-4.55)	-2686.0 (-1.50)	13669.1*** (2.95)
Per Capita Income (in 2015 $US)$_t$	271.5*** (19.73)	271.5*** (6.74)	124.4*** (3.86)
Minimum State Corporate Income Tax$_t$	117.2*** (2.71)	117.2 (1.07)	-161.3** (-2.54)
Year$_t$	-104.7** (-2.44)	-104.7* (-1.85)	31.73 (0.92)
Constant$_t$	273852.3*** (3.14)	273852.3** (2.44)	-182819.5** (-2.03)
N	364	364	364
R^2	0.77	0.77	0.01

t-statistics are in parentheses
*: significant at 10% level, **: significant at 5% level, ***: significant at 1% level
Fixed Effects R^2 is the overall R^2
Data Sources include: Bureau of Labor Statistics (2018), National Science Foundation (2017), National Science Foundation (2018), Tax Foundation (2013), Tax Foundation (2015), U.S. Census Bureau (2016), U.S. Census Bureau (2017), U.S. Department of Education (2018), and U.S. Patent and Trademark Office (2017)
OLS estimates linear regression models

Table 5: Regression Results for the Natural Logarithm of High-Technology Employment at the MSA Level and Stratified by Geographic Region, 2000-2015

	Robust Standard Errors		Clustered Robust Standard Errors	
	Midwestern Cities	New England Cities	Midwestern Cities	New England Cities
Graduate Students in STEM fields$_{t-1}$ (in thousands)	-0.148*** (-3.91)	0.431*** (3.07)	-0.148 (-1.60)	0.431 (1.27)
Undergraduate Students in STEM fields$_{t-1}$ (in thousands)	0.190*** (5.93)	-0.293*** (-5.52)	0.190* (2.01)	-0.293** (-2.38)
Undergraduate Students not in STEM fields$_{t-1}$ (in thousands)	-0.0114*** (-3.90)	-0.0481*** (-5.97)	-0.0114 (-1.33)	-0.0481 (-1.77)
Natural Logarithm of R&D expenditures in Science and Engineering$_t$ (in millions of 2015 $US)	0.144*** (4.88)	-0.665*** (-5.59)	0.144 (1.64)	-0.665* (-2.03)
Patents issued to a University$_{t-1}$	-0.00557 (-1.52)	0.00869 (0.96)	-0.00557 (-0.90)	0.00869 (0.92)
Patents issued to a University$_{t-2}$	-0.00562 (-1.51)	0.0164* (1.84)	-0.00562 (-1.18)	0.0164** (2.68)
Natural Log of City Population$_t$	0.841*** (11.70)	3.643*** (6.52)	0.841*** (3.82)	3.643* (2.08)
Per Capita Income (in 2015 $US)$_t$	0.0646*** (8.94)	0.00753*** (3.32)	0.0646*** (4.24)	0.00753 (1.57)
Minimum State Corporate Income Tax$_t$	-0.0482*** (-4.52)	0.201** (2.45)	-0.0482 (-1.66)	0.201 (1.37)
Year$_t$	0.00383 (0.67)	0.0194 (1.33)	0.00383 (0.44)	0.0194 (0.82)
Constant$_t$	-11.44 (-1.00)	-69.94** (-2.60)	-11.44 (-0.68)	-69.94* (-1.89)
N	238	126	238	126
R^2	0.82	0.67	0.82	0.67

t-statistics are in parentheses
*: significant at 10% level, **: significant at 5% level, ***: significant at 1% level
Fixed Effects R^2 is the overall R^2
Data Sources include: Bureau of Labor Statistics (2018), National Science Foundation (2017), National Science Foundation (2018), Tax Foundation (2013), Tax Foundation (2015), U.S. Census Bureau (2016), U.S. Census Bureau (2017), U.S. Department of Education (2018), and U.S. Patent and Trademark Office (2017)
OLS estimates linear regression models

Table 6: Regression Results for the Natural Logarithm of Overall Employment at the MSA Level and Stratified by Geographic Region, 2000-2015

	Robust Standard Errors		Clustered Robust Standard Errors	
	Midwestern Cities	New England Cities	Midwestern Cities	New England Cities
Graduate Students in STEM fields$_{t-1}$ (in thousands)	-0.133*** (-6.03)	0.211*** (2.88)	-0.133** (-2.18)	0.211 (1.25)
Undergraduate Students in STEM fields$_{t-1}$ (in thousands)	0.141*** (6.56)	-0.356*** (-11.00)	0.141** (2.14)	-0.356*** (-5.22)
Undergraduate Students not in STEM fields$_{t-1}$ (in thousands)	-0.00627*** (-2.80)	-0.00532 (-1.20)	-0.00627 (-0.97)	-0.00532 (-0.38)
Natural Logarithm of R&D expenditures in Science and Engineering$_t$ (in millions of 2015 $US)	0.115*** (6.36)	-0.402*** (-6.29)	0.115* (2.00)	-0.402** (-2.44)
Patents issued to a University$_{t-1}$	-0.00530** (-2.45)	0.00766 (1.52)	-0.0053 (-1.46)	0.00766 (1.34)
Patents issued to a University$_{t-2}$	-0.00803*** (-3.59)	0.0140*** (2.89)	-0.00803** (-2.53)	0.0140*** (5.33)
Natural Log of City Population$_t$	0.822*** (17.82)	3.350*** (11.31)	0.822*** (5.8)	3.350*** (3.82)
Per Capita Income (in 2015 $US)$_t$	0.0464*** (10.73)	-0.000156 (-0.11)	0.0464*** (3.98)	-0.000156 (-0.06)
Minimum State Corporate Income Tax$_t$	-0.0217*** (-3.72)	0.0779* (1.84)	-0.0217* (-1.77)	0.0779 (1.05)
Year$_t$	-0.0116*** (-3.44)	0.0127 (1.47)	-0.0116*** (-3.10)	0.0127 (1.08)
Constant$_t$	23.81*** (3.48)	-50.31*** (-3.08)	23.81*** (3.18)	-50.31** (-2.73)
N	238	126	238	126
R^2	0.88	0.79	0.88	0.79

t-statistics are in parentheses
*: significant at 10% level, **: significant at 5% level, ***: significant at 1% level
Fixed Effects R^2 is the overall R^2
Data Sources include: Bureau of Labor Statistics (2018), National Science Foundation (2017), National Science Foundation (2018), Tax Foundation (2013), Tax Foundation (2015), U.S. Census Bureau (2016), U.S. Census Bureau (2017), U.S. Department of Education (2018), and U.S. Patent and Trademark Office (2017)
OLS estimates linear regression models

Table 7: Regression Results for the Average High-Technology Wage at the MSA Level and Stratified by Geographic Region, 2000-2015

	Robust Standard Errors		Clustered Robust Standard Errors	
	Midwestern Cities	New England Cities	Midwestern Cities	New England Cities
Graduate Students in STEM fields$_{t-1}$ (in thousands)	-1352.1*** (-3.26)	-991.7 (-1.02)	-1352.1 (-1.66)	-991.7 (-0.59)
Undergraduate Students in STEM fields$_{t-1}$ (in thousands)	-185.7 (-0.58)	1837.9*** (3.46)	-185.7 (-0.22)	1837.9* (2.16)
Undergraduate Students not in STEM fields$_{t-1}$ (in thousands)	-203.2*** (-5.30)	-350.3*** (-6.35)	-203.2* (-2.02)	-350.3** (-2.48)
Natural Logarithm of R&D expenditures in Science and Engineering$_t$ (in millions of 2015 $US)	1478.5*** (5.15)	512.3 (0.65)	1478.5* (1.98)	512.3 (0.35)
Patents issued to a University$_{t-1}$	15.1 (0.37)	-141.8** (-2.37)	15.1 (0.30)	-141.8** (-2.73)
Patents issued to a University$_{t-2}$	9.838 (0.22)	30.03 (0.48)	9.838 (0.20)	30.03 (0.54)
Natural Log of City Population$_t$	2716.3*** (3.28)	-14115.4*** (-4.01)	2716.3 (1.48)	-14115.4* (-2.27)
Per Capita Income (in 2015 $US)$_t$	990.7*** (13.77)	312.6*** (19.5)	990.7*** (11.71)	312.6*** (13.32)
Minimum State Corporate Income Tax$_t$	-467.0*** (-3.96)	650.9 (1.16)	-467.0 (-1.66)	650.9 (0.95)
Year$_t$	67.17 (1.06)	268.6** (2.8)	67.17 (0.68)	268.6 (1.43)
Constant$_t$	-130421.5 (-1.01)	-305988.3* (-1.66)	-130421.5 (-0.66)	-305988.3 (-0.90)
N	238	126	238	126
R^2	0.45	0.79	0.45	0.79

t-statistics are in parentheses
*: significant at 10% level, **: significant at 5% level, ***: significant at 1% level
Fixed Effects R^2 is the overall R^2
Data Sources include: Bureau of Labor Statistics (2018), National Science Foundation (2017), National Science Foundation (2018), Tax Foundation (2013), Tax Foundation (2015), U.S. Census Bureau (2016), U.S. Census Bureau (2017), U.S. Department of Education (2018), and U.S. Patent and Trademark Office (2017)
OLS estimates linear regression models

Table 8: Regression Results for the Average Overall Wage at the MSA Level and Stratified by Geographic Region, 2000-2015

	Robust Standard Errors		Clustered Robust Standard Errors	
	Midwestern Cities	New England Cities	Midwestern Cities	New England Cities
Graduate Students$_{t-1}$ (in thousands)	735.7*** (3.74)	1863.0*** (3.35)	735.7** (2.17)	1863.0* -2.23
Undergraduate Students in STEM fields$_{t-1}$ (in thousands)	167.3 (1.07)	-162.0 (-0.45)	167.3 (0.40)	-162.0 (-0.37)
Undergraduate Students not in STEM fields$_{t-1}$ (in thousands)	-99.2*** (-6.07)	-209.4*** (-6.93)	-99.2** (-2.81)	-209.4** (-4.44)
Natural Logarithm of R&D expenditures in Science and Engineering$_t$ (in millions of 2015 $US)	89.7 (0.66)	-1913.5*** (-4.41)	89.7 (0.24)	-1913.5** (-2.66)
Patents issued to a University$_{t-1}$	-2.796 (-0.12)	5.894 (0.20)	-2.796 (-0.13)	5.894 (0.19)
Patents issued to a University$_{t-2}$	43.24 (1.67)	0.388 (0.01)	43.24** (2.43)	0.388 (0.02)
Natural Log of City Population$_t$	288.5 (0.69)	-1731.4 (-0.91)	288.5 (0.29)	-1731.4 (-0.46)
Per Capita Income (in 2015 $US)$_t$	318.2*** (7.38)	175.4*** (13.59)	318.2*** (3.51)	175.4*** (10.05)
Minimum State Corporate Income Tax$_t$	-224.0*** (-5.00)	264.0 (0.86)	-224.0*** (-3.26)	264.0 (0.53)
Year$_t$	-80.51** (-2.45)	36.19 (0.52)	-80.51 (-1.51)	36.19 (0.28)
Constant$_t$	191088.5*** (2.83)	1486.9 (0.01)	191088.5 (1.74)	1486.9 (0.01)
N	238	126	238	126
R^2	0.67	0.85	0.67	0.85

t-statistics are in parentheses
*: significant at 10% level, **: significant at 5% level, ***: significant at 1% level
Fixed Effects R^2 is the overall R^2
Data Sources include: Bureau of Labor Statistics (2018), National Science Foundation (2017), National Science Foundation (2018), Tax Foundation (2013), Tax Foundation (2015), U.S. Census Bureau (2016), U.S. Census Bureau (2017), U.S. Department of Education (2018), and U.S. Patent and Trademark Office (2017)
OLS estimates linear regression models

Table 9: Cities and Metropolitan Statistical Areas (MSA's) used in study

City	State	MSA	Region
Bridgeport	Connecticut	Bridgeport-Stamford-Norwalk, CT	New England
New Haven	Connecticut	New Haven, CT	New England
Stamford	Connecticut	Bridgeport-Stamford-Norwalk, CT	New England
Hartford	Connecticut	Hartford-West Hartford-East Hartford, CT	New England
Waterbury	Connecticut	Waterbury, CT	New England
Rockford	Illinois	Rockford, IL	Midwest
Springfield	Illinois	Springfield, IL	Midwest
Peoria	Illinois	Peoria, IL	Midwest
Fort Wayne	Indiana	Fort Wayne, IL	Midwest
Evansville	Indiana	Evansville, IN-KY	Midwest
South Bend	Indiana	South Bend-Mishawaka, IN-MI	Midwest
Worcester	Massachusetts	Worcester, MA-CT	New England
Springfield	Massachusetts	Springfield, MA-CT	New England
Lowell	Massachusetts	Lowell-Billerica-Chelmsford, MA-NH NECTA Division	New England
Grand Rapids	Michigan	Grand Rapids-Wyoming, MI	Midwest
Ann Arbor	Michigan	Ann Arbor, MI	Midwest
Lansing	Michigan	Lansing-East Lansing, MI	Midwest
Buffalo	New York	Buffalo, NY	Midwest
Rochester	New York	Rochester, NY	Midwest
Syracuse	New York	Syracuse, NY	Midwest
Cincinnati	Ohio	Cincinnati	Midwest
Toledo	Ohio	Toledo, OH	Midwest
Akron	Ohio	Akron, OH	Midwest
Dayton	Ohio	Dayton, OH	Midwest
Allentown	Pennsylvania	Allentown-Bethlehem-Easton, PA-NJ	Midwest
Providence	Rhode Island	Providence-Warwick, RI-MA	New England

Table 10: Summary Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
Number of Graduate Students in STEM Fields (in Thousands)	1.72	1.43	0.00	7.11
Number of Undergraduate Students in non-STEM fields (in Thousands)	25.30	12.80	1.72	57.69
Number of Undergraduate Students in STEM fields (in Thousands)	3.95	2.13	0.17	11.51
University Expenditures in Science & Engineering R&D (in millions of $US 2015)	219.06	270.16	0.00	1340.59
Number of University Patents	13.17	18.39	0.00	122.00
Per Capita Personal Income (in thousands of $US 2015)	47.93	16.15	34.04	114.75
Minimum State Corporate Income Tax	6.68	2.66	0.26	10.00
City Population	162,705.40	59,863.23	100,913.00	329,898.00
Overall Employment Level	318,107.10	192,944.50	63,150.00	1,032,580.00
High-Technology Employment Level	15,334.95	11,263.98	1,080.00	62,870.00
Average High-Tech Wage Level (in $US 2015)	77,115.31	9,115.81	54,852.29	105,486.80
Average Wage Level (in $US 2015)	47,860.97	5,819.02	38,249.63	68,060.67
Number of Observations: 416	Observations per City: 16	Number of Cities: 26		

Table 11: Summary Statistics Stratified by Region

Midwest				
Variable	Mean	Standard Deviation	Minimum	Maximum
Number of Graduate Students in STEM Fields (in Thousands)	1.51	1.51	0.00	7.11
Number of Undergraduate Students in non-STEM fields (in Thousands)	22.44	13.90	1.72	57.69
Number of Undergraduate Students in STEM fields (in Thousands)	3.83	2.52	0.17	11.51
University Expenditures in Science & Engineering R&D (in millions of $US 2015)	177.44	276.62	0.00	1340.59
Number of University Patents	11.83	20.33	0.00	122.00
Per Capita Personal Income (in thousands of $US 2015)	41.15	3.33	34.04	51.40
Minimum State Corporate Income Tax	5.78	2.84	0.26	10.00
City Population	175,638.00	68,179.99	100,913.00	329,898.00
Overall Employment Level	321,935.30	205,323.10	103,640.00	1,032,580.00
High-Technology Employment Level	14,718.20	11,706.18	3,000.00	62,870.00
Average High-Tech Wage Level (in $US 2015)	72,562.92	5,164.82	54,873.46	84,096.66
Average Wage Level (in $US 2015)	44,836.51	2,885.93	38,249.63	54,840.54
Number of Observations: 272	Observations per City: 16		Number of Cities: 17	

New England				
Variable	Mean	Standard Deviation	Minimum	Maximum
Number of Graduate Students in STEM Fields (in Thousands)	2.12	1.19	0.36	4.51
Number of Undergraduate Students in non-STEM fields (in Thousands)	30.72	7.99	15.52	43.89
Number of Undergraduate Students in STEM fields (in Thousands)	4.17	1.04	2.08	7.67
University Expenditures in Science & Engineering R&D (in millions of $US 2015)	297.67	239.35	5.74	816.48
Number of University Patents	15.69	13.74	0.00	62.00
Per Capita Personal Income (in thousands of $US 2015)	60.72	22.00	38.72	114.75
Minimum State Corporate Income Tax	8.40	0.83	7.00	9.50
City Population	138,277.10	25,913.67	103,668.00	184,491.00
Overall Employment Level	310,876.20	167,524.70	63,150.00	623,190.00
High-Technology Employment Level	16,499.93	10,316.24	1,080.00	40,870.00
Average High-Tech Wage Level (in $US 2015)	85,714.26	8,759.41	54,852.29	105,486.80
Average Wage Level (in $US 2015)	53,573.83	5,676.29	44,295.32	68,060.67
Number of Observations: 144	Observations per City: 16	Number of Cities: 9		

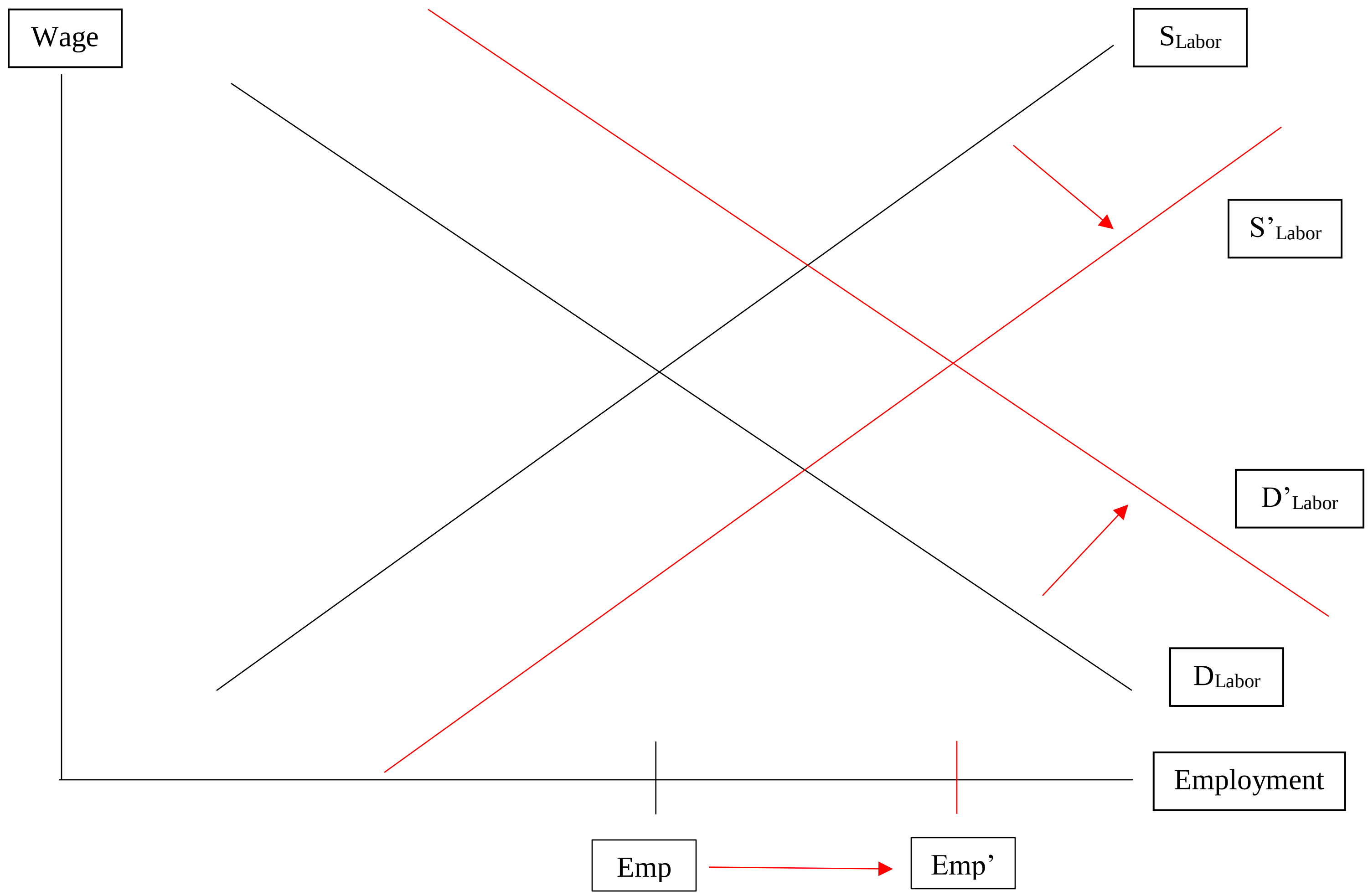
Table 12: List of Universities Included in Study

Fairfield University	Central Connecticut State University	Springfield College-School of Professional and Continuing Studies	Syracuse University
Albertus Magnus College	Charter Oak State College	University of Massachusetts-Amherst	Upstate Medical University
Sacred Heart University	Quinnipiac University	Western New England University	Art Academy of Cincinnati
Southern Connecticut State University	Southern Connecticut State University	Westfield State University	Cincinnati Christian University
St Vincent’s College	University of Connecticut-Tri-Campus	Bentley University	Cincinnati College of Mortuary Science
University of Bridgeport	University of New Haven	Brandeis University	Gods Bible School and College
University of Connecticut-Stamford	Wesleyan University	Merrimack College	Good Samaritan College of Nursing and Health Science
University of New Haven	Yale University	Northpoint Bible College	Miami University-Hamilton
Western Connecticut State University	Beloit College	Regis College	Mount Saint Joseph University
Yale University	Rockford University	Rivier University	Northern Kentucky University
Albertus Magnus College	Saint Anthony College of Nursing	Thomas More College of Liberal Arts	The Christ College of Nursing and Health Sciences
Fairfield University	St. John’s College-Department of Nursing	Tufts University	Thomas More College
Quinnipiac University	University of Illinois at Springfield	University of Massachusetts-Lowell	Union Institute & University
Sacred Heart University	Bradley University	Aquinas College	University of Cincinnati-Blue Ash College
Southern Connecticut State University	Eureka College	Calvin College	University of Cincinnati-Clermont College

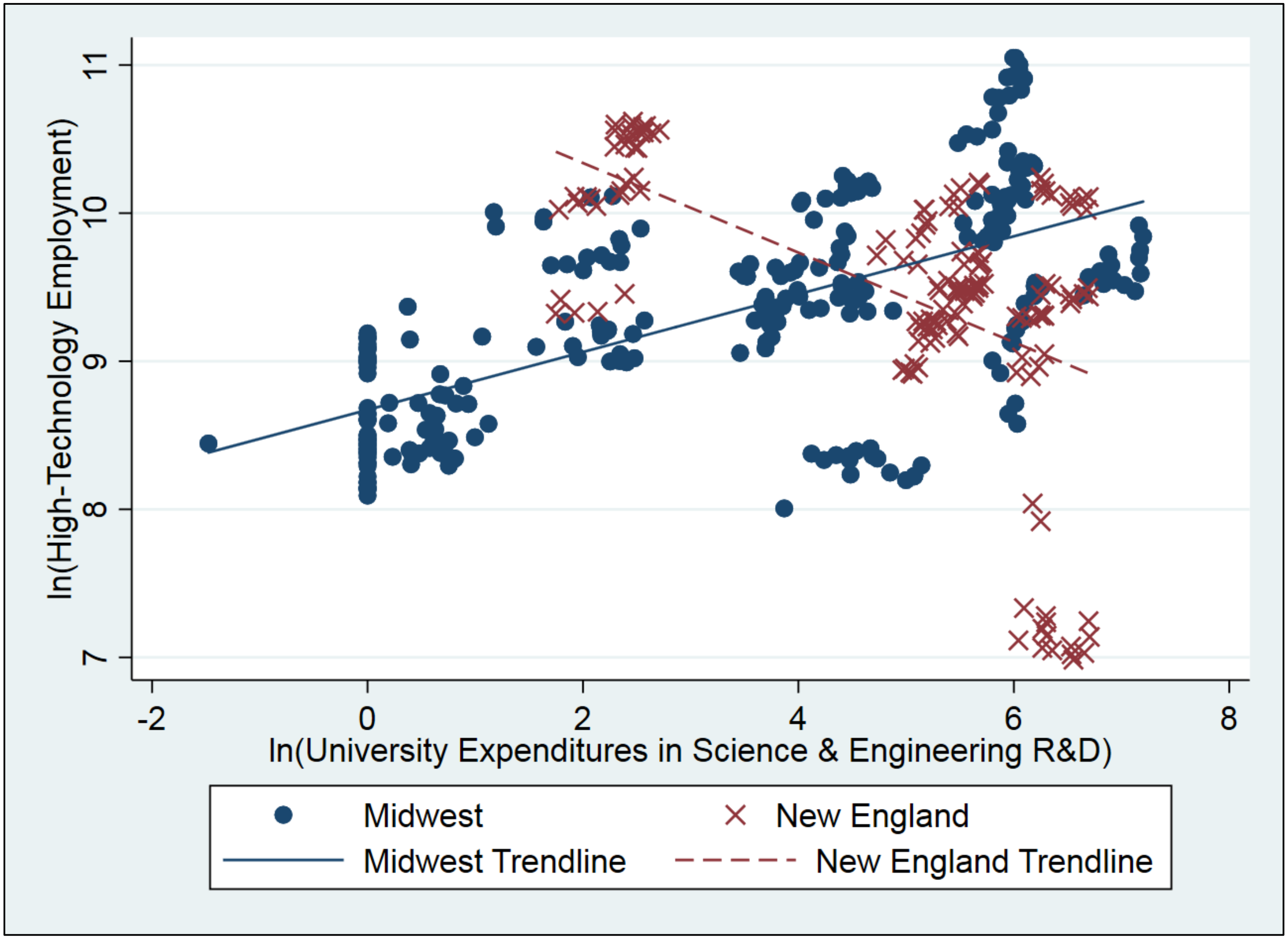
St Vincent's College	Methodist College	Compass College of Cinematic Arts	University of Cincinnati-Main Campus
University of Bridgeport	Saint Francis Medical Center College of Nursing	Cornerstone University	Xavier University
University of Connecticut-Tri-Campus	Huntington University	Davenport University	Bowling Green State University-Main Campus
University of New Haven	Indiana Institute of Technology	Grace Bible College	Lourdes University
Yale University	Indiana University-Purdue University-Fort Wayne	Grand Valley State University	Mercy College of Ohio
Concordia College-New York	Trine University-Regional/Non-Traditional Campuses	Kuyper College	University of Toledo
Fairfield University	University of Saint Francis-Fort Wayne	Eastern Michigan University	Kent State University at Kent
Iona College	University of Evansville	Madonna University	Kent State University at Stark
Kehilath Yakov Rabbinical Seminary	University of Southern Indiana	University of Michigan-Ann Arbor	Malone University
LIU Post	Bethel College- Indiana	Great Lakes Christian College	Stark State College
Manhattanville College	Holy Cross College	Michigan State University	University of Akron Main Campus
Mercy College	Indiana University-South Bend	Canisius College	Walsh University
New York College of Health Professions	Saint Mary's College	Daemen College	Antioch University-Midwest
New York Institute of Technology	University of Notre Dame	D'Youville College	Cedarville University
Sacred Heart University	Anna Maria College	Hilbert College	Central State University
Sarah Lawrence College	Assumption College	Medaille College	Kettering College
SUNY at Purchase College	Becker College	Niagara University	University of Dayton
SUNY College at Old Westbury	Clark University	SUNY Buffalo State	Wilberforce University

The College of New Rochelle	College of the Holy Cross	Trocaire College	Wright State University-Main Campus
University of Bridgeport	Framingham State University	University at Buffalo	Cedar Crest College
University of Connecticut-Stamford	Nichols College	Villa Maria College	DeSales University
Webb Institute	Worcester Polytechnic Institute	Nazareth College	Kutztown University of Pennsylvania
Yeshiva of Nitra Rabbinical College	Worcester State University	Roberts Wesleyan College	Lafayette College
Central Connecticut State University	American International College	Rochester Institute of Technology	Lehigh University
Charter Oak State College	Amherst College	Saint John Fisher College	Moravian College
Goodwin College	Bay Path University	SUNY College at Brockport	Muhlenberg College
Holy Apostles College and Seminary	College of Our Lady of the Elms	Talmudical Institute of Upstate New York	Pennsylvania State University-Penn State Lehigh Valley
Trinity College	Hampshire College	University of Rochester	Brown University
University of Hartford	Mount Holyoke College	Cazenovia College	Bryant University
University of Saint Joseph	Smith College	Le Moyne College	Dean College
Wesleyan University	Springfield College	SUNY College of Environmental Science and Forestry	Johnson & Wales University-Providence
Albertus Magnus College			

Graph 1: Impact of Increases in Labor Demand and Supply on Employment and Wage Levels

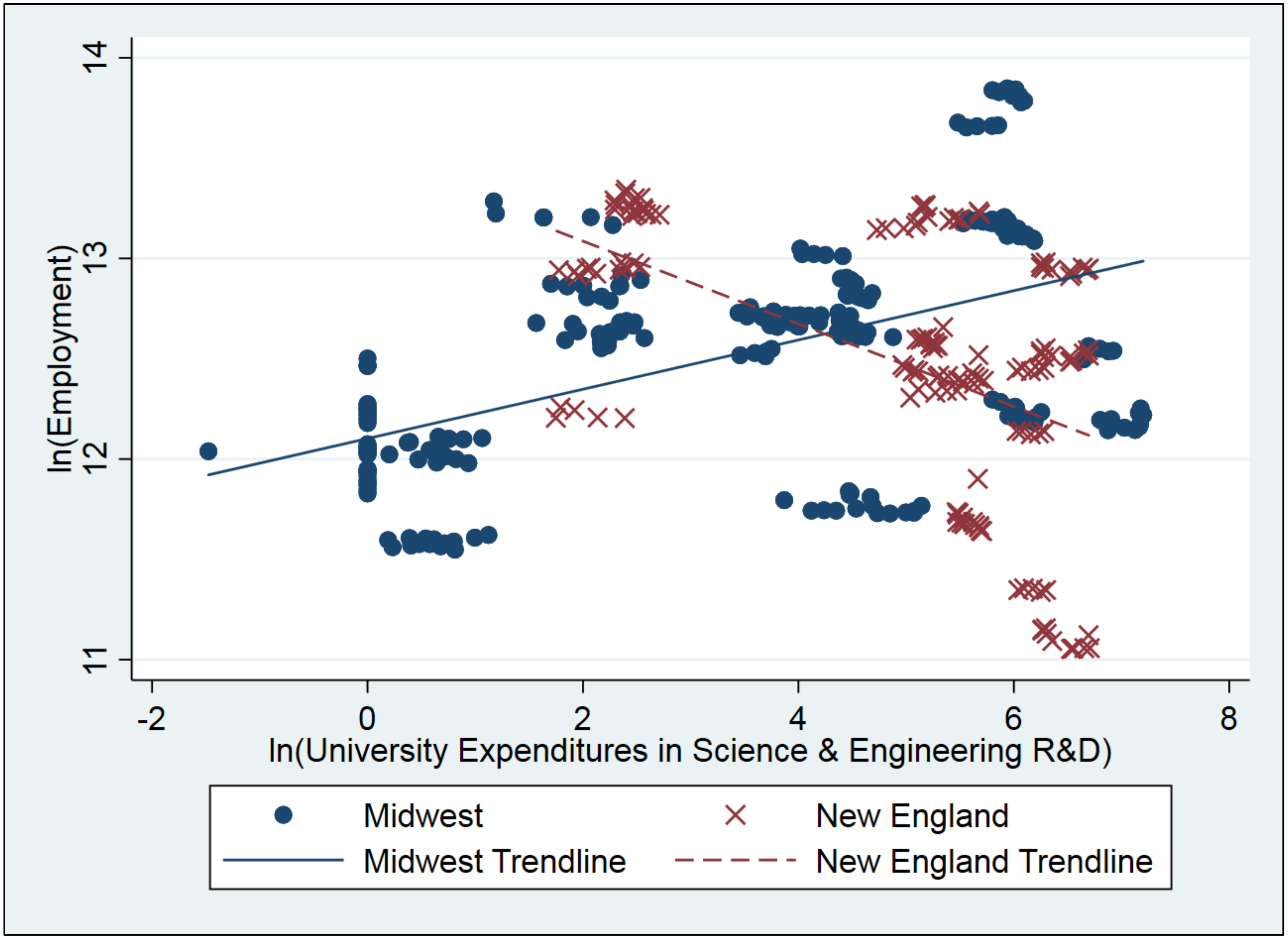


Graph 2: The Relationship Between *ln*(University R&D Expenditures) and *ln*(High-Technology Employment). At the MSA Level and Separated by Region



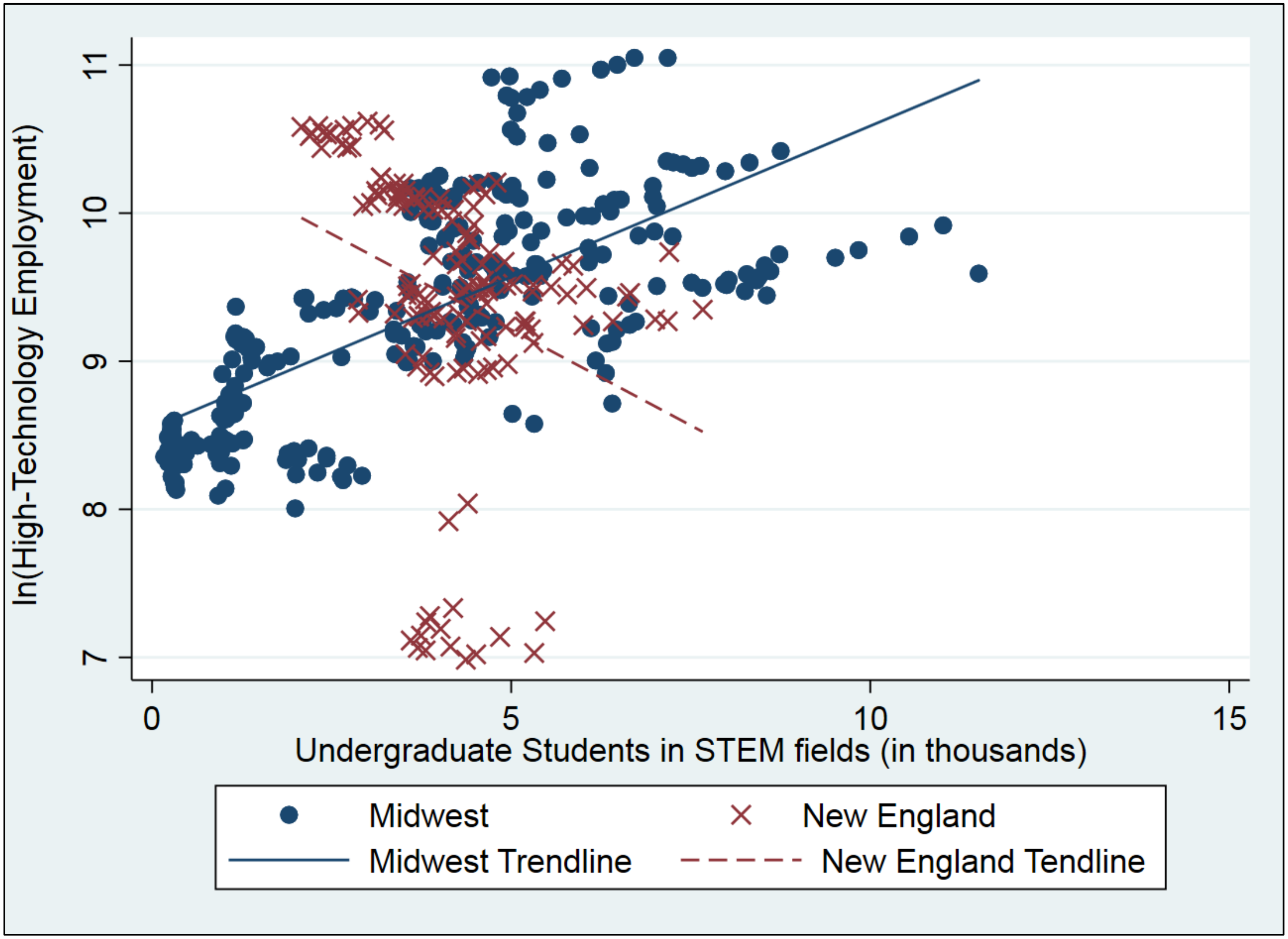
Sources: Bureau of Labor Statistics (2018) and U.S. Department of Education (2018)

Graph 3: The Relationship Between *ln*(University R&D Expenditures) and *ln*(Employment).
At the MSA Level and Separated by Region



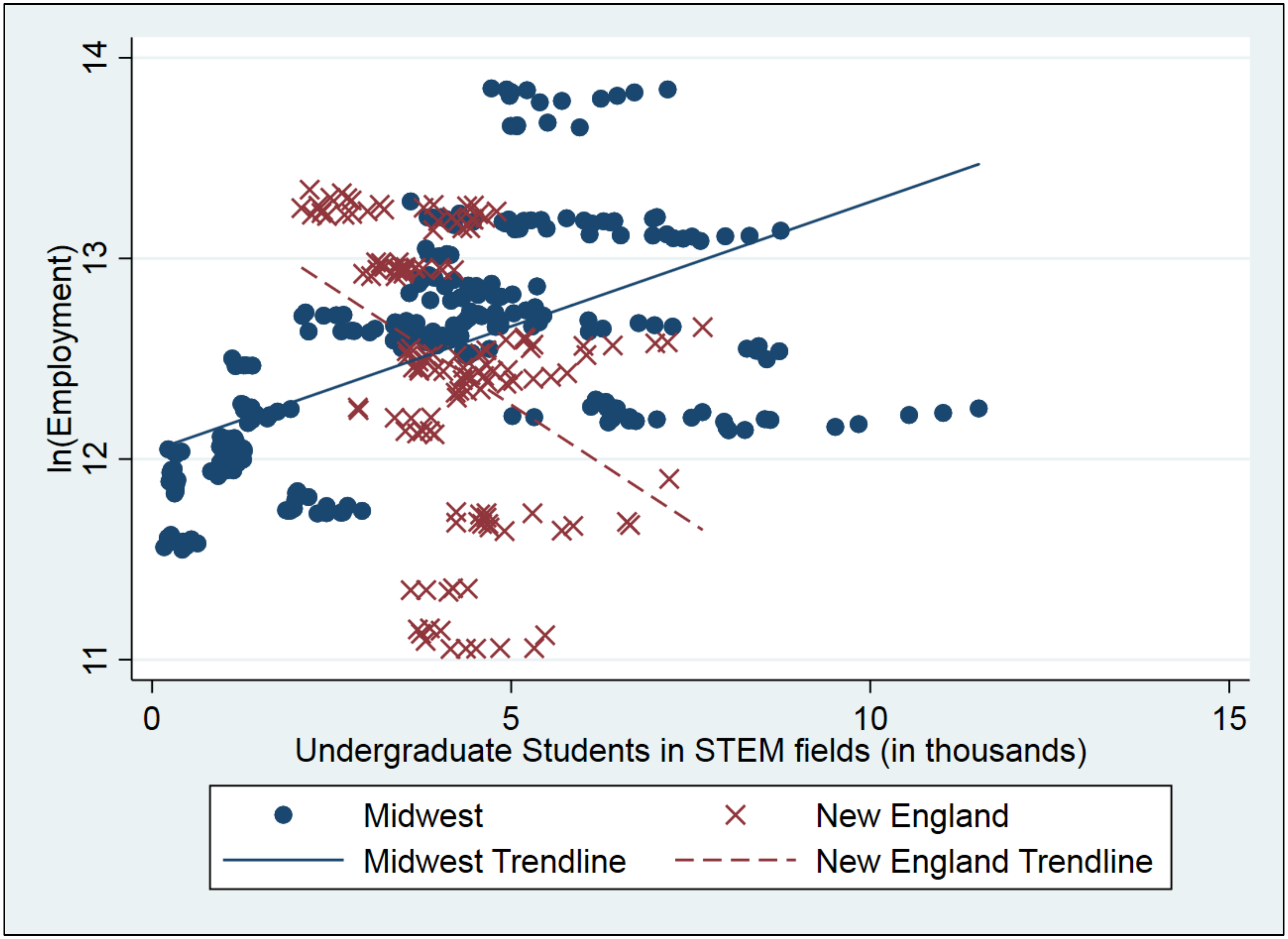
Sources: Bureau of Labor Statistics (2018) and U.S. Department of Education (2018)

Graph 4: The Relationship Between the Number of STEM Undergraduates and *ln*(High-Technology Employment).
At the MSA Level and Separated by Region



Sources: Bureau of Labor Statistics (2018) and U.S. Department of Education (2018)

Graph 5: The Relationship Between the Number of STEM Undergraduates and *ln*(Employment).
At the MSA Level and Separated by Region



Sources: Bureau of Labor Statistics (2018) and U.S. Department of Education (2018)

Map 1: Map of Cities Used in this Study

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